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Literature search on machine learning applied to autonomous vehicular driving: A review

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ABSTRACT
This work aims to explore the various industrial and research initiatives about the application of Artificial Intelligence (AI) techniques to autonomous vehicle driving. In particular, it is highlighted in the Autonomous Vehicle (AV) study that the transition to an era of data abundance demands a paradigm shift from physics-based models to AI-guided methods, capable of predicting future traffic dynamics and assisting in the formulation of optimized traffic policies, whose potential lies in factors such as the reduction of human errors and the rapid response to accidents in real time, These factors justify the present study. Autonomous driving transcends traditional traffic patterns by performing tasks such as proactively recognizing critical events, planning next moves, making decisions, and performing control tasks to ensure passenger safety and comfort in dynamic traffic environments. The levels of vehicular automation are presented and focuses on AI-guided methods focused on End-to-End structures over pipeline structures, exploring details about MLP (Multi-Layer Perceptron) and KAN (Kolmogorov–Arnold Networks) Neural Network architectures, the main concepts and strategies that guide these techniques, as well as future challenges related to AVs. Therefore, it is concluded that technologies such as machine learning, deep learning, reinforcement learning, as well as the joint use of these, are essential for the implementation of AV control systems that promote the evolution of the transportation system.

Keywords: Machine learning, Reinforcement learning, Deep learning, Artificial Intelligence, Machine learning, Autonomous vehicles, Intelligent vehicles.

INTRODUCTION

Numerous industrial and research initiatives have been undertaken to improve vehicle safety, prevent accidents, and predict the outcomes of road and vehicle accidents. Among the strategies, the use of autonomous vehicles stands out for its potential to prevent human error and respond promptly to accidents in real time [1]. Autonomous driving transcends conventional traffic patterns, proactively recognizing critical events in advance, ensuring the safety of passengers, and providing them with comfortable transportation, especially in highly stochastic and variable traffic environments [2]. Technologies based on machine learning, deep learning, and artificial intelligence are vital for self-driving cars. The reason why Artificial Intelligence (AI) is rapidly being deployed in a number of industries is that it has the ability to learn and solve problems on its own [3]. In self-driving cars, AI applications can be deployed in conjunction with advanced technological innovations such as GPS, radar, camera, cloud services, and control signals [4]. The transition from an era of data scarcity to a data-rich era (*big data*) is

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taking place, and as a result, there is an urgent need for a methodological paradigm shift from physics-based models to AI-driven methods that can design future traffic dynamics composed of AVs traveling alongside human-powered vehicles (VH) and assist in the formulation of socially optimized policies [5]. Physics-based models refer to all scientific hypotheses about the movement of cars or traffic flow, while AI-guided methods reflect cutting-edge models that mimic human intelligence, including deep neural networks, reinforcement learning, imitation learning, and other advanced machine learning methods [5]. This work focuses on AI-guided methods and applies a methodology of review of the main points surrounding the proposed theme.

OBJECTIVE

This work aims to explore the various industrial and research initiatives on the application of AI techniques to autonomous vehicular driving. The transition to an era of data abundance demands a paradigm shift from physics-based models to AI-driven methods capable of predicting future traffic dynamics and assisting in the formulation of optimized traffic policies, the potential of which lies in factors such as the reduction of human errors and the rapid response to accidents in real time. These factors justify the present study.

METHODOLOGY

In this article we bring a holistic view of the main principles of AI and their applications in the context of autonomous vehicles, discussing the international standard of vehicle automation levels and focusing on AI methods applied to End-to-End Frameworks guided by machine learning, rather than Pipeline frameworks. We also explore details about the architectures of MLP (*Multi-Layer Perceptron*) and KAN (*Kolmogorov–Arnold Networks*) Neural Networks, the main concepts and strategies that guide these techniques, as well as limitations of these architectures. Finally, we list some of the main challenges and future perspectives taken from this research, both from the point of view of scientific research and the market, among other aspects related to Machine Learning (*ML*), Deep Learning (DL), Reinforcement *Learning (*RL), as well as the joint use of these in the implementation of AVs.

DEVELOPMENT

Autonomous driving transcends traditional traffic patterns by performing tasks such as proactively recognizing critical events, planning next moves, making decisions, and performing control tasks to ensure passenger safety and comfort in dynamic traffic environments. In the following sections, we'll delve into the application of AI to autonomous driving.

AUTONOMOUS VEHICULAR DRIVING

Research on Autonomous Driving Systems has been gaining importance in recent decades, enormously revolutionizing the automotive industry [6]. AI systems make use of data and algorithms to impersonate the cognitive functions of the human brain [3]. AI is making our daily lives more convenient and efficient, and is essentially the effort to produce systems with human-like cognitive behavior, such as the ability to reason, solve a problem, discover meaning and perceive past experiences, and act coherently [4]. There is a growing interest in this field, as the deployment of autonomous vehicles on the roads promises safer and greener transport systems [1]. Vehicle control is one of the most critical challenges in autonomous vehicles and connected and automated vehicles, and is critical to vehicle safety, passenger comfort, transportation efficiency, and energy savings [7]. The problems of conventional automobiles, such as lack of road safety, low independence of people with disabilities, high costs, less productivity, traffic congestion, long travel time, and environmental pollution can be avoided with autonomous car driving through the application of AI [4]. Specific groups of people who are unable to drive, such as the elderly, young people or people with disabilities will be able to enjoy the mobility promoted by this technology. Another relevant aspect of the application of autonomous driving is that it can also help to make driving more efficient, reducing fuel consumption and, consequently, a lower adverse impact on the environment [6]. An urban traffic environment consists of traffic entities, including cars, traffic lights, pedestrians, cyclists, scooters, and other road users. This multimodal mixed traffic environment further complicates the control of autonomous vehicles circulating alongside multiple road users [5]. While vehicle automation has already led to great achievements in supporting the driver in a number of monotonous and challenging tasks, it is observed that, for example, increasing the level of automation to fully automated driving is an extremely challenging problem. This is mainly due to the complexity of real-world environments, including obstacle avoidance and aspects of human driving behavior [8]. In the era of mixed autonomy, when AVs circulate alongside human-driven vehicles [5], according to [9], the primary purpose of self-driving cars is to mitigate accidents and human errors, thereby increasing road safety.

By seeking to reduce the human errors that motivate accidents such as driver inattention, distraction or drunkenness, autonomous driving has the potential to save thousands of lives, since autonomous vehicles are designed to perform appropriate maneuvers in order to, among others, eliminate the risk of accidents [6]. Humans are prone to fatigue, inattention, and drowsiness. Additionally, the use of in-vehicle technologies such as smartphones, entertainment systems, and navigation can take away the driver's attention and compromise driving safety. Therefore, the costs of road accidents to society are high in terms of human injuries and economic losses [1]. As pointed out in [10], approximately 1.19 million people died in road crashes in 2023 worldwide. Also according to the World Health Organization (WHO), 90% of all traffic deaths occur in low- and middle-income countries, such as Latin American nations.

According to the report [11], 392,000 people died in Brazil as a result of traffic accidents between 2010 and 2019, an increase of 13.5% compared to the previous decade. Corroborating these data, the report [11] by the National Road Safety Observatory points out that Brazil ended 2017 with 35,375 deaths, a figure that cost the national coffers about 62 billion reais. Also according to this latest report, in total, projections estimate that spending on traffic accidents by 2027 would result in an accumulated of 640 billion reais and that 90% of accidents occur due to human errors, ranging from inattention to disrespect for traffic legislation. Thus, it is observed that research related to AVs is justified by its potential to provide alternatives that aim to ensure more comfort and safety to users, in addition to facilitating the locomotion of specific groups of individuals and, as presented in this article, AI is a key piece in the context of AV control.

CONTEXTUALIZING AUTONOMOUS VEHICULAR DRIVING

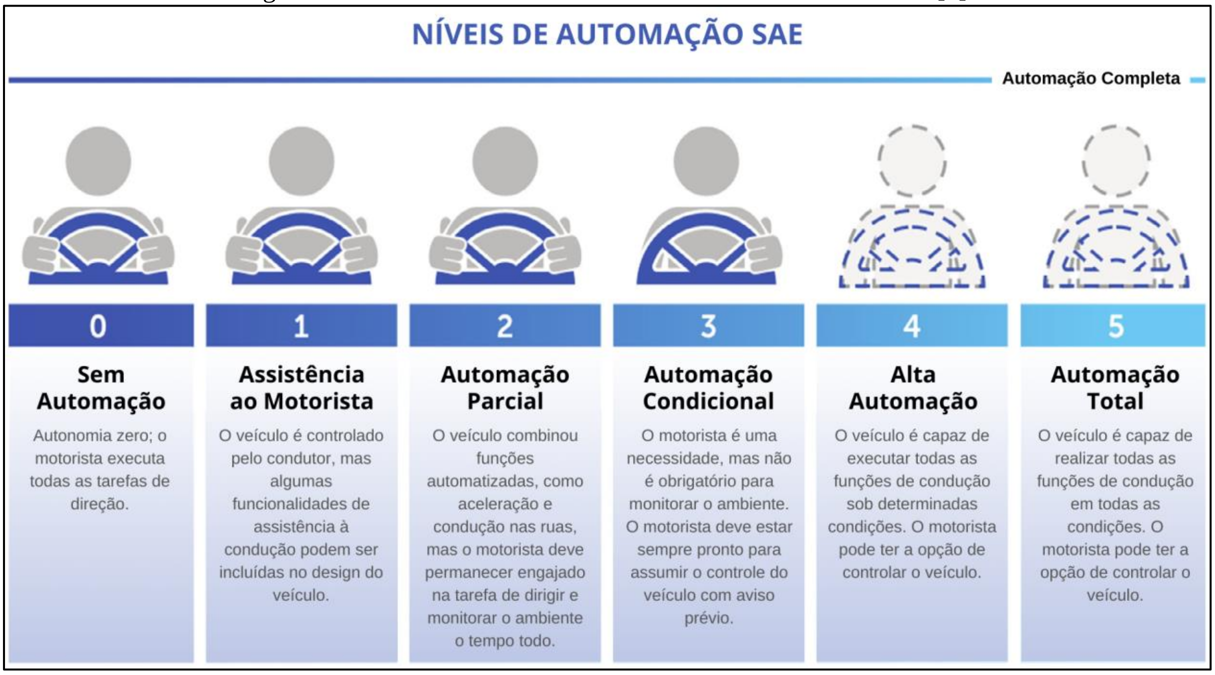
Autonomous driving refers to the ability of a vehicle to circulate partially or fully without human intervention [2]. With the emergence of computationally powerful AI techniques, autonomous vehicles can detect their environment with high accuracy, make safe decisions in real-time, and operate more reliably without human interventions [13]. The AV deployment stage can be divided into four phases of different modeling complexity: pure human-driven (VH) vehicles, VH-dominated, AV-dominated, and pure AVs, highlighting that the modeling of these phases encompasses game theory, deep learning, and imitation learning [5]. Through the joint working group between the *Society of Automotive Engineers* (SAE *International*) and the International *Organization for Standardization* (ISO) called SAE/ISO, representatives from nine countries work collaboratively on a consistent normative document for use across the global mobility community called SAE-J3016 [14] which, as pointed out in [5, 6, 15], defines a taxonomy for six levels of automation of driving in the context of motor vehicles and their operation on the roads: from Level 0 (without driving automation) to Level 5 (full driving automation). These six levels of SAE J3016 vehicle automation have been schematized in [15], as follows:

a. Level 0: The individual operator is responsible for all operational activities (no automation).
b. Level 1: The vehicle is controlled by a human driver, but the automation system assists in the operation (assistance to drivers).
c. Level 2: The vehicle uses automated features, but the control and environment of the driving process requires human intervention (partially automated driving).
d. Level 3: The human driver must be ready to take control of the vehicle at any time (automated conditional driving).
e. Level 4: Under some conditions, the automation system can drive the car automatically, but the human operator will still be able to control it (high-level driving automation).

f. Level 5: Under all conditions, the automation system can drive the car automatically, but the human operator will be able to control it (fully automated driverless cars).

Figure 1 [6] illustrates the levels of vehicle automation according to the SAE J3016 standard.

Fig. 1. SAE J3016 Vehicle Automation Levels. Translated from [6].



In [1] a distinction is made between passive and active safety systems, citing seat belts and airbags as passive safety systems and elucidating the fact that these systems have become standard safety equipment for vehicles, but that they are reactive solutions, i.e. those used after an accident has occurred. As a result, active safety technologies are becoming a topic of discussion among car manufacturers and researchers. According to [15], several researchers and organizations are trying to achieve level 5 automation, and among those developing research, the main companies: Google, Argo AI, Nvidia, Mercedes Benz, Ford, Volvo, Lyft and Aptiv, as well as universities and other research-oriented institutions.

The operational framework for operating autonomous vehicles in dynamic and unpredictable traffic scenarios necessitates meticulous orchestration of data collection and processing through a series of software-driven layers. This process encompasses wide-ranging tasks: data collection and processing through sensors, the perception phase, entailing the recognition and interpretation of prevailing environmental circumstances and the execution of control planning [9]. Figure 2 [9] represents the *Sensing*, *Perception*, *Planning*, and *Control* tasks in the context of autonomous vehicles, illustrating distinct layers of software that are unique to the AV, a feature that is absent in the domain of conventional vehicles.

Fig. 2. Tasks in autonomous vehicles. Translated from [9].

Within the domain of autonomous vehicle systems, different safety paradigms are implemented and characterize into distinct categories: the first category belongs to the granular layer of nodes, tools, and components within the system. Here, the solutions are independent of communication and the use of complex data sets. The second category investigates security considerations in the system and levels of communication. It meticulously examines critical factors and formulates solutions within the complexities of the network and system, underpinned by existing road safety data [9]. Automation and connectivity are two distinct technologies. AVs may or may not have connectivity, while connected vehicles may or may not have automation. Connected vehicle refers to vehicle technology that allows users to communicate with each other within surface transportation ecosystems [5].

Vehicle driving choices contain three levels: operational level (including pedal control and braking), tactical level (comprising lane keeping and lane change), and strategic level (including routing). Operational and tactical controls can be further categorized into longitudinal control (i.e., car following, lane keeping) and lateral control (i.e., lane change), respectively [5, 15]. This work provides a holistic view on these three levels of conduction.

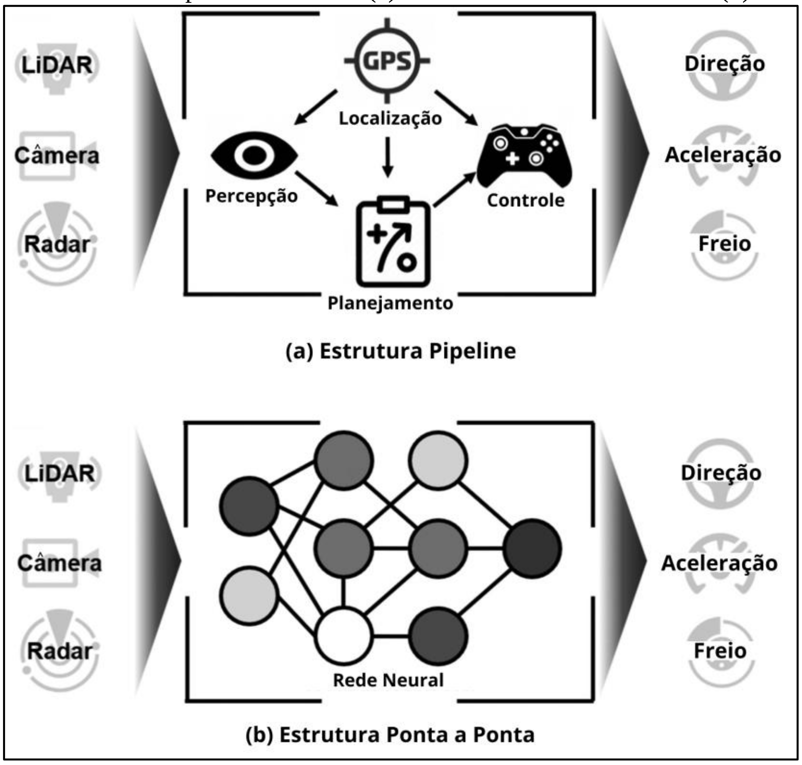
ARTIFICIAL INTELLIGENCE APPLIED TO AUTONOMOUS VEHICLES: RELEVANT CONCEPTS AND STRATEGIES

Before continuing the study on AI applied to AVs, it is important to pay attention to two frameworks that, according to [2, 16, 17], stand out in the context of autonomous vehicle driving research: the modular pipeline framework and the end-to-end *framework*. The first consists of several submodules, each with specific functionality, while the second represents a simplified single-module (modular pipeline) approach [2]. In the context of motion planning for autonomous driving, the pipeline planning method, also known as the rules-based planning method, is a well-established category of planners [16].

The modular architecture is widely used in autonomous driving system approaches, which divides the driving pipeline into discrete sub-tasks. This architecture relies on individual sensors and algorithms to process data and generate control outputs, encompassing interconnected modules including perception, planning, and control, but which, however, has certain drawbacks that prevent further advances in autonomous driving [2, 17]. Modular pipelines often involve redundancy of calculations, as each module is trained for task-specific outcomes, and a significant limitation of pipeline architecture is its susceptibility to error propagation from one module to a subsequent one, which can lead to unsafe behaviors. The complexity of managing the interconnected modules and the computational inference of data processing at each step pose additional challenges [2]. A significant advantage of the pipeline structure is its interpretability, allowing for the identification of faulty modules when malfunctions or unexpected system behavior occur. Although widely used in industry, the pipeline planning method requires substantial computational resources and numerous heuristic functions [16]. The Modular Pipelines approach involves sophisticated rules-based designs, which are often ineffective in dealing with the large number of situations that occur on the road, and therefore there is a growing trend to harness large-scale data and use learning-based planning as a viable alternative [17], referring to the End-to-End approach.

The End-to-End approach has a simplified architecture, which consists of one or a few networks and also offers superior robustness and real-time capabilities compared to the pipeline structure [16]. Compared to modular pipelines, End-to-End frameworks benefit from joint optimization of resources for insight and planning [17]. This approach is a promising paradigm as it circumvents the disadvantages associated with modular systems, such as their enormous complexity and propensity to propagate errors and aims to overcome the limitations of modular architecture, so as to simplify the system, improving efficiency and robustness, by directly mapping the sensory input to control the outputs, so as to optimize the conduction pipeline [2]. The autonomous driving community has witnessed rapid growth in approaches that adopt an End-to-End algorithm framework, utilizing raw information from sensors to generate vehicle motion plans, rather than focusing on individual tasks such as motion detection and prediction [17]. In an end-to-end approach, rather than assembling a system based on components that are tuned individually, one builds the system and then tunes its performance together [18]. The benefits of end-to-end autonomous driving have attracted significant attention in the research community [2]. However, [16] points out that as research progresses, End-to-End optimization faces a critical interpretability problem. Without intermediate results, tracing the initial cause of an error and explaining why the model arrived at specific control commands or trajectories becomes more challenging. The End-to-End approach simplifies the system, improving efficiency and robustness by directly mapping input sensory data to control outputs [2]. Figure 3 [16] represents the Modular Pipeline and End-to-End approaches.

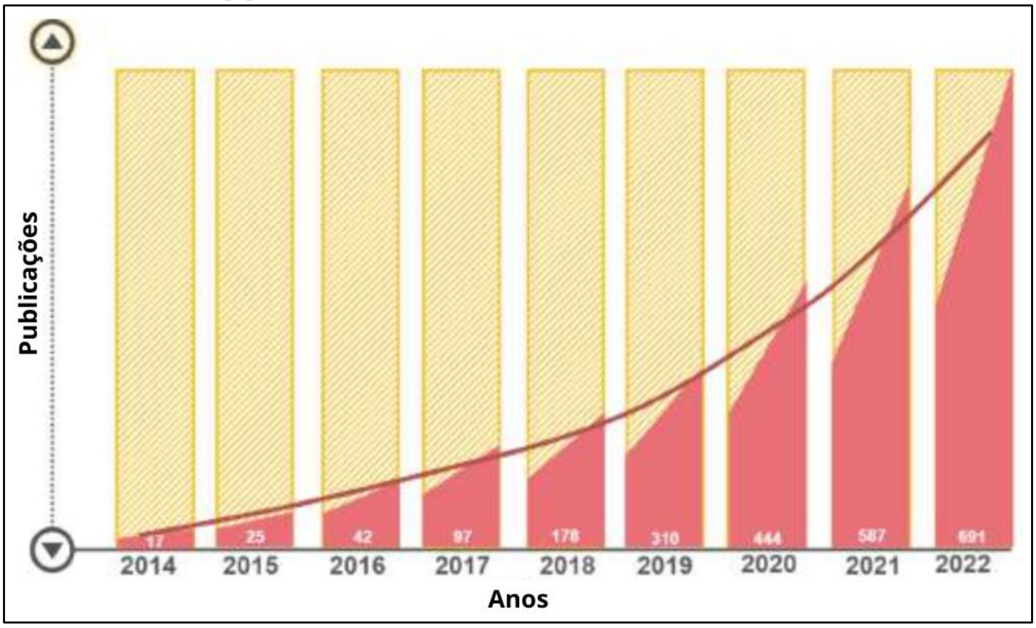
Fig. 3. Comparison between the Pipelines structure (a) and the End-to-End structure (b). Translated from [16].



The Pipeline framework for autonomous driving can be summarized as a set of interconnected modules, while the End-to-End method treats the whole context as a learnable framework [16]. In addition to the End-to-End approach aiming to overcome the limitations of modular architecture, it is a growing trend in the research community [2], as the number of articles in the Web of Science database containing the keywords "*End-to-End*" and "*Autonomous Driving*" illustrated in Figure 4 [2].

Self-driving cars are essentially built with artificial intelligence [4]. Overall, it has been shown that various AI approaches can provide promising solutions for AVs in recognizing the environment and propulsion of the vehicle with proper decision-making [19]. The fundamental pillars of AI that underpin the existence of self-driving cars are: Machine Learning, Deep Learning, Internet of Things (IoT), Computer Vision, and Cognitive Capabilities [3]. This paper focuses on the first two concepts.

Fig. 4. Number of articles in the Web of Science database containing the keywords 'End-to-End' and 'Autonomous Driving' from 2014 to 2022. Translated from [2].



MACHINE LEARNING

One of the main tasks of an ML algorithm in a self-driving car is the continuous detection of the surrounding environments and the calculation of the possible changes in those environments [3]. All machine learning is concerned with extracting information from data and typically requires working with large datasets [18]. ML refers to the ability of a machine to understand and learn a specific task and make decisions without human intervention and, eventually, improve itself to perform the same task by gaining experience without using explicit programming, and machine learning can be divided into two types: *Supervised Learning* (SL) and Unsupervised *Learning (Unspervised Learning*, US) [3].

Supervised learning (SL) is summarized in [20] as the act of learning from a set of labeled training examples provided by a qualified external supervisor. SL involves the analysis of a dataset and the known results [3]. This definition is reinforced by [18] when stating that SL addresses the task of predicting labels with input features, where each feature-label pair is called an example. Supervision comes into play because for the choice of parameters, supervisors provide the model with a dataset consisting of labeled examples, where each example is matched with the fundamental truth label [18].

On the other hand, unsupervised learning (US) is used in the case of unclassified and unlabeled data [3]. The terms supervised learning and unsupervised learning seem to exhaustively classify machine learning paradigms, but they do not, and therefore we consider reinforcement learning (RL) to be a third machine learning paradigm, along with supervised learning, unsupervised learning, and perhaps other paradigms as well [20]. This work addresses the most relevant ML concepts and paradigms for the field of study focused on vehicle autonomy.

SL approaches rely heavily on large amounts of labeled data to be able to generalize and are basically trained on each task in isolation, however, obtaining a large amount of data for each individual task in autonomous driving is costly and time-consuming, requiring enormous human labor to label this data, and even then may not cover all the complex situations of real-world driving [21].

REINFORCEMENT LEARNING

Reinforcement Learning *(*RL) is a field of trial-and-error learning that has been successfully applied in end-to-end driving when combined with SL [17]. RL is capable of learning by trial and error and does not require explicit human labeling or oversight on each data sample, instead needing a well-defined reward function to receive reward signals in its learning process [21]. The purpose of RL is expressed as reward functions, and many algorithms require them to be dense and provide feedback at each step of the environment [17]. The reward is required in almost all reinforcement learning algorithms and estimates how well the agent performs an action in a given state (or what the good or bad things are for the agent) [22].

Performing RL in real-world AVs is a challenging task [16]. RL algorithms learn by sensing the environment directly and do not have access to the transition dynamics (i.e., prior knowledge) of the explored environment [13]. In the RL framework, an agent interacts with the environment in a sequence of actions (selected following a specific policy), observations, and rewards [8]. RL algorithms aim to learn a policy, which is a map from states to actions, based on the response received from interaction with the environment [23]. RL methods are used for maintenance and control of various aspects of connected autonomous vehicles, such as setting specific angular positions for driving [15]. At each time step t, the agent (VA) observes the state of the st ∈ S environment and, based on a specific policy, selects an action at at ∈ A, where S is the state space and A = {1,..., K} is the set of available actions. Then, the agent observes the new state of the environment, st + 1, which is the consequence of applying the action at to the state st, and a scalar reward signal rt, which is a quality measure of how good it is to select the action at in state st [8]. RL is different from supervised learning, the type of learning studied in most current research in the field of machine learning, as well as being different from unsupervised learning, which is typically about finding hidden structures in collections of unlabeled data, i.e., even if it is not based on examples of correct behaviors. RL tries to maximize a reward signal rather than trying to find a hidden structure [20].

DEEP LEARNING

Deep Learning (DL) is a solution to more intuitive and complex problems that cannot be easily solved using classical methods [3]. AI approaches, predominantly in terms of deep learning algorithms, have brought considerable improvements to many key components (perception, object detection, planning) of autonomous driving technology [13]. DL is profound exactly in the sense that its models learn from many layers of transformations, where each layer provides representation at one level [18], i.e., models are trained using multiple layers of input data [15].

The advent of deep learning (DL) has enabled many studies to address different challenging issues in AVs, e.g., accurately recognizing and locating obstacles on roads, making appropriate decisions (e.g., controlling the steering wheel, acceleration/deceleration), etc [19]. Preferred DL models used in self-driving car technology include *End-To-End Learning*, Convolutional Neural Network *(*CNN), Deep Convolutional Neural Network (*Deep* CNN), *Fully Convolutional Networks* (FCN), *Deep Neural Network* (DNN), Deep Reinforcement Learning (*Deep* Boltzmann Machine (DBM), *Belief* Networks, and *Deep Autoencoders* [3]. Among the applications of DL in the context of AVs, it can be mentioned according to [15] that DL allows AVs to perceive a stop signal or differentiate a user from an electric pole. As per [1], some studies have used autonomous implementations of deep learning for banner detection problems, while some research focuses on merging deep learning with other machine learning techniques and classical methodologies.

The simplest deep networks are called multilayer perceptrons, and they consist of several layers of neurons each fully connected to those in the layer below (from which they receive contributions) and those above (which they, in turn, influence). This architecture is commonly referred to as a multi-layer perceptron, often abbreviated as MLP (*Multi-Layer Perceptron*) [18]. Utilizing the backpropagation algorithm for training, they can be used for a wide range of applications, from functional approximation to prediction in diverse fields [24]. MLP adds one or several fully connected hidden layers between the output and input layers, and transforms the output of the hidden layer via an activation function [18].

The multilayer perceptron is the most well-known and most frequently used type of neural network. Most of the time, signals are transmitted within the network in one direction: from input to output. There is no loop, the output of each neuron does not affect the neuron itself. Multilayer perceptrons (MLPs), also known as fully connected feedforward neural networks [24], are the fundamental building blocks of current deep learning models [25]. Figure 5 [18] depicts an MLP Network as well as its input, output, and hidden layer layers.

The cost of parameterization of MLPs with fully connected layers can be prohibitively high, which can motivate trade-off between parameter saving and model effectiveness, even without changing the input or output size [18]. In this sense, a network architecture called KAN (*Kolmogorov–Arnold Networks*) with a promising approach is proposed in [25], as compared to MLP networks and KAN networks presented in Figure 6 [25].

The KAN Network presents itself as a new neural network architecture designed to potentially replace traditional multilayer perceptrons [26]. Like MLPs, KANs have fully connected structures.

However, while MLPs place fixed activation functions on nodes ("neurons"), KANs place activation functions that can be learned at the edges ("weights"). As a result, KANs have no linear weight matrix: instead, each weight parameter is replaced by a learning matrix [25]. Unlike MLPs, which are inspired by the universal approximation theorem, KANs take advantage of this representation theorem to generate a different architecture [26].

Fig. 5. Representation of an MLP Network in the form of a diagram. Translated from [18].

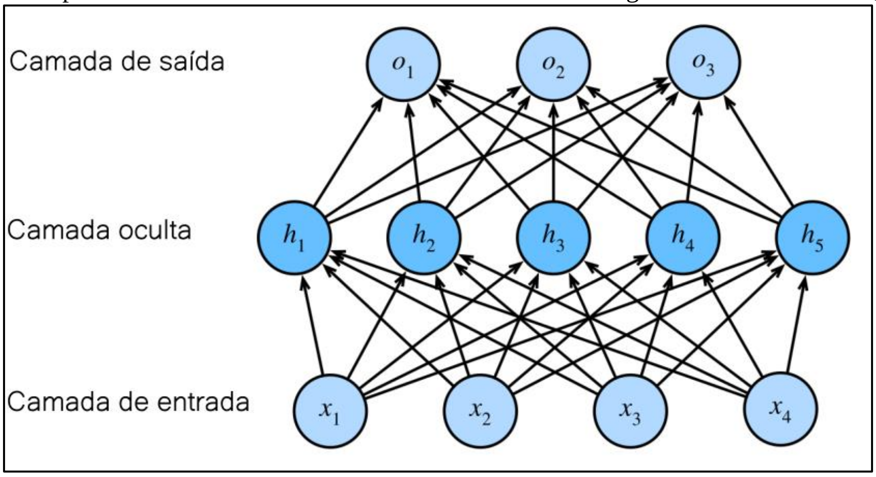
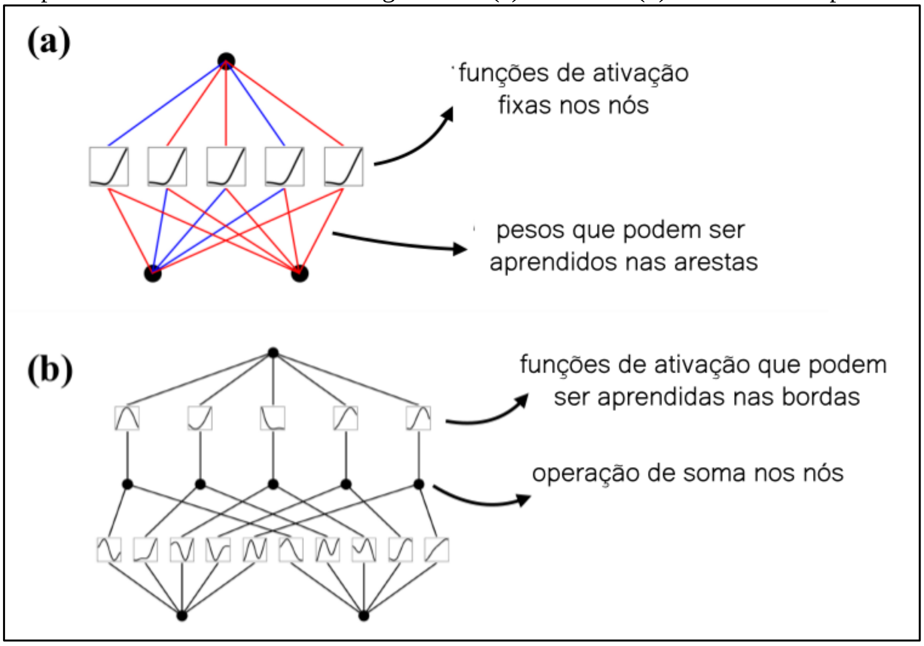


Fig. 6. Representation of models according to MLP (a) and KAN (b) networks. Adapted from [25].



DEEP REINFORCEMENT LEARNING

The use of deep algorithms in conjunction with other techniques has shown promising results [1], such as *Deep Reinforcement Learning* (DRL), where deep learning is applied to reinforcement learning problems [18]. The combination of DL techniques and RL algorithms has demonstrated its potential to solve some of the most challenging tasks of autonomous driving [27]. The main goal of LR is to statistically maximize long-term reward [28]. DRL can be defined as a combination of DL and RL [3, 27, 28], emerging as a potential solution to the limitations of modern AV trajectory tracking control algorithms [7] and, as pointed out by [18], its application has become popular DRL further enhances reinforcement learning using deep learning and multilayer neural networks [15].

Early decision-making strategies were rule-based, but they were not adequate to cover all scenarios, and as deep learning technology reaches maturity, DRL, which exhibits great representativeness and optimization capabilities, holds promise for the development of decision-making strategies for automated vehicles [29]. By implementing a deep reinforcement learning algorithm, VAs learn an optimal control policy by interacting with the environment and utilizing the data collected [7]. It can be difficult for the algorithm to learn from all the states and determine the reward path. In this sense, DRL-based algorithms replace tabular methods of estimating state values (all possible state and value pairs must be stored) with an approximation function that allows the VA to generalize the value of states it has never seen before, or has partially seen, using the values of similar states [27]. Comprehensive use of in-depth separable convolution along with transformer in DRL-based architectures for lane change decision inference can yield an optimal policy [30].

Generally, in the DRL framework, the agent is able to drive in an uncertain environment by selecting a sequence of actions over several continuous time steps. Subsequently, it will grant rewards based on the feedback of the interaction with the environment. Finally, a strategy with maximum cumulative reward will be chosen [30]. DRL algorithms include: *Deep Q-learning Network* (DQN), Double-DQN, Actor-Critical (A2C, A3C), *Deep Deterministic Policy Gradient* (DDPG), and DDPG with Double Delay (TD3) [27].

RELEVANT MACHINE LEARNING ALGORITHMS, THEORETICAL APPROACHES, AND STRATEGIES

AVs have emerged as a promising technology for improving road safety and mobility. However, designing AVs involves several critical aspects, such as software and system requirements, which must be carefully addressed [9]. AI can completely replace humans with automation with better safety and intelligent vehicle movement, so intelligent software and tools are necessary for the efficient design and development of AVs [15]. Software and system requirements are among the aspects that require consideration when creating vehicles. Although these aspects are of minimal importance in traditional vehicles, self-driving cars can potentially cause damage, accidents and compromise safety [9]. The Autonomous Driving System involves many subsystems that need to be integrated as a larger system. Some of the tasks include motion planning, vehicle location, pedestrian detection, traffic sign detection, road markings detection, automated parking, vehicle cybersecurity, and system fault diagnosis [6]. Recent years have witnessed the emergence of approaches and solutions that use data sensors to collect real-time information from the surroundings [9]. These systems anticipate events, predict accidents, and assess environmental conditions, thus enabling automated decision-making at various levels of autonomous driving.

AI is a critical technology for the efficient functionality of autonomous vehicles, which use it in conjunction with sensory technologies and minimize risk. In the field of object detection, computer vision, and semantic segmentation, deep learning has been very effective [15]. In traditional software, operational logic is written manually and then tested in a series of test cases, while in the case of DNN-based software, the software learns and adapts to certain situations with the help of large data sets [3]. The accuracy rate of AI approaches, such as DNN, reached the value of 99.46% and surpassed human recognition in some tests [19]. Advanced Neural Networks are used to predict the malfunction of sensors, such as prediction, identification, and isolation of faulty sensors [4]. The DL approach has become more popular than ML due to its effective performance in both classification and detection, using image frames as input to the network algorithm [1]. 63% of the studies reviewed use various AI methods, with LD being the most prevalent (34%) [9].

RL algorithms in the control context have been mainly used to solve the optimal regulation and tracking of single-agent and multi-agent systems [23]. Automatic decision-making approaches, such as RL, have been applied to control vehicle speed, among other tasks in the context of AVs [22]. Most real-world dynamical systems, including unmanned vehicles, are inherently nonlinear. Finding the optimal solution for nonlinear systems requires solving a nonlinear partial differential equation, namely the Hamilton-Jacobi-Bellman (HJB) equation. Explicitly solving the HJB equation is usually very difficult or even impossible. Reinforcement learning is one of the most commonly used techniques to approximate the HJB solution, and is therefore widely used in unmanned vehicle systems [23].

PERCEPTION, MOVEMENT PLANNING, DECISION MAKING AND CONTROL

Four significant modules are contained in autonomous vehicles: perception, decision-making, planning, and control [31]. It is essential that the vehicle recognises its own circumstances and adapts to them in order to be able to drive automatically [22]. The trajectory generation module leverages perception information to calculate a set of future trajectories [16]. Perception is thought of as an AV action that uses sensors to continuously scan and monitor the environment, similar to human vision and other senses [19], indicating that autonomous vehicles know information about driving environments based on that of a variety of sensors, such as Radar, LiDAR (*Light Detection and Ranging*), and Global *Positioning System*, GPS) [31]. In the case of current algorithms, the processes of perception and planning are combined for behavior-conscious planning, many of which rely on machine learning [6]. Planning methods are responsible for calculating a sequence of trajectory points for the VA's low-level controller to track, typically consisting of three functions: global route planning, local behavior planning, and local trajectory planning [16].

DRL algorithms have been widely employed as independent motion planning or control modules for autonomous vehicles [21]. In the area of movement planning, the final rewards of the episode are calculated from the fulfillment or failure of the directing task [28]. The goal of planning for trajectory questions is usually to find a possible relationship from the original state to reaching a target state [6]. Several approaches to the control layer of an AV have been developed, which are commonly classified into classical controller and AI-based controllers. The difference in terms of applicability between these controllers is that while purely conventional control techniques offer deterministic behavior, AI-based controllers have stochastic behavior due to the fact that they learn from a certain set of features [27]. A controller defines the speed, steering angle, and braking actions required at each point of the path obtained from a predetermined map, such as Google Maps, or specialized driving record of the same values at each reference point. Trajectory tracking, in contrast, involves a temporal model of vehicle dynamics visualizing landmarks sequentially over time [32].

Trajectory planning is a crucial module in the autonomous driving process. Given a route level plan from HD maps or GPS-based maps, this module is required to generate motion-level commands that guide the agent [32]. Despite a significant amount of machine learning efforts dedicated to computer vision, the intelligence of AVs lies in their optimal decision-making in the movement planning phase [5]. The decision-making function that receives the information from the environment and generates high-level intentions for VA is a crucial component in the elaboration of the driving strategy [29]. Deep reinforcement learning has shown great success in the area of vehicle behavioral decision-making, especially in highway and intersection scenarios [21]. DRL unites function approximation and target optimization by mapping state-action pairs to expected rewards [27]. The decision-making controller manages the driving behaviors of vehicles and these behaviors include accelerating, braking, changing and keeping lanes, and so on [31].

CHALLENGES AND FUTURE DIRECTIONS

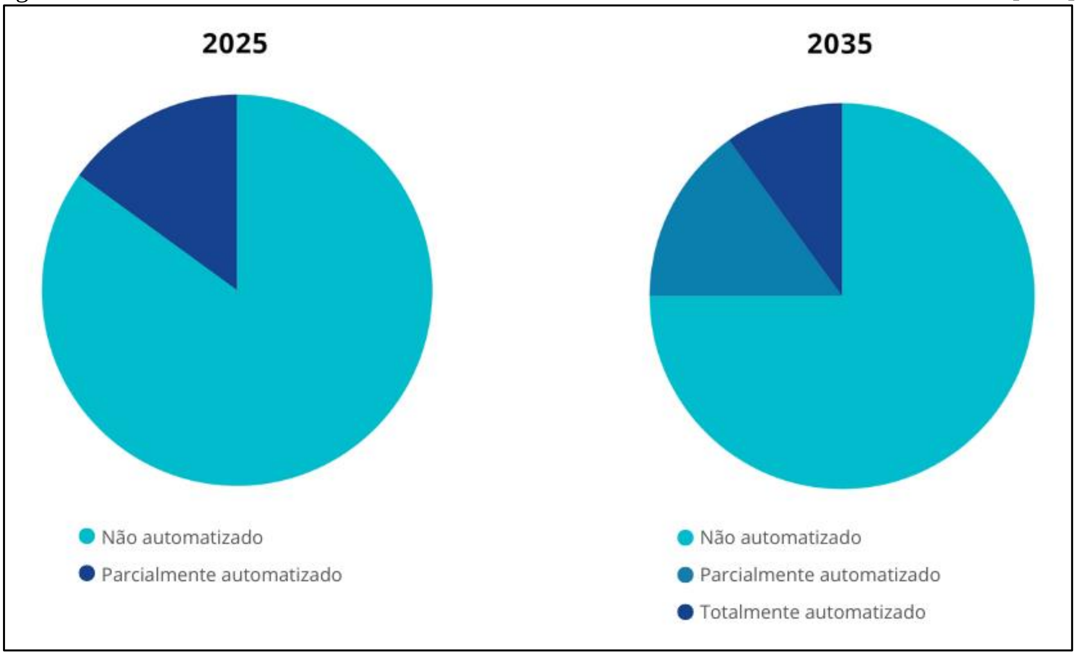
Despite the remarkable contributions of leading experts in the field, Intelligent Vehicles remain mostly confined to limited test programs due to concerns about their reliability and safety [16]. AI-powered self-driving cars face challenges such as social acceptability, road conditions, traffic, weather, data privacy, and cybersecurity [4]. AVs will have substantial impacts over time, even if they are still in development. Thus, there is a need to study safety precautions before accepting them in real environments

[15]. Ensuring the safety, robustness and adaptability of planning methods become crucial for the successful implementation of autonomous driving systems [16].

By 2035, driverless vehicles are expected to account for 25% of total car sales, with 15% being partially autonomous and 10% fully autonomous, compared to 12.4% in 2025. According to most industry experts, North America will become the leading market for autonomous vehicles. The United States will be the leader in the autonomous vehicle market [4, 33]. Figure 7 [4, 33] presents a comparison between the number of autonomous, partially automated and non-automated vehicles in the years 2025 and 2035.

Future research may also explore ways to improve feedback mechanisms, allowing users to understand the decision-making process and instill confidence in the reliability of end-to-end driving systems [2]. Human driving habits affect drivers' decision-making performance and therefore the inclusion of human driving habits in the design of autonomous driving systems may improve the acceptance of emerging technologies by drivers, and this scenario is a likely target of future research [30].

Fig. 7. The share of autonomous vehicle sales in the market in 2025 and 2035. Translated from [4:33].



As for the choice of the optimal architecture for deep networks, future research may define which ones should be adopted for specific situations. Currently, the biggest bottleneck of KANs lies in their slowness in training. KANs are generally slower than MLPs, given the same number of parameters. Therefore, the slow training of KANs can be seen more as an engineering problem to be improved in the future, rather than a fundamental limitation [25], and this information may give us some clue about future research on deep network architectures and their applications.

From a legal point of view, it should be noted that, at the time this article is constructed, the Brazilian legislation does not yet have a law that regulates the AVs. Currently, the main legal reference for the circulation of autonomous vehicles in Brazil is Bill 1,317/2023, which aims to regulate the use of autonomous vehicles throughout the national territory and is still pending in the Chamber of Deputies. In addition, Resolution 479/2018 of the National Traffic Council (Contran) defines responsibilities and rules regarding the performance of tests with AVs and minimum safety requirements, which can guide and facilitate the testing of prototypes of Brazilian AVs. As a consequence, this legal loophole can lead to negative deadlocks in VA research and testing. According to [15], it is necessary for legislators to create legislation that benefits the country economically and socially, and complements by stating that studies examine the potential of AVs to become a "killer app" with dramatic consequences.

FINAL THOUGHTS

This article presented a literature search on machine learning applied to autonomous vehicular driving, reviewing the main points surrounding the topic, providing an overview of the applications of AI in AVs, the main challenges, future directions, public perception, current scenario of the AV market, in addition to presenting growth projections for the area for the next decade. The main research and industry initiatives that permeate the study directed to AVs were pointed out, evidencing the significant advance of research related to the theme in recent years.

The focus on AI-guided methods represents a promising evolution in the quest for a safer and more efficient transportation system. In AVs, AI models are integrated with technologies such as GPS, LiDAR, Radar, cameras, cloud services and control signals, responsible for understanding the environment in which the intelligence agent is inserted, in order to make the best decisions and provide assertive responses in real time. Advanced machine learning methods, such as deep learning (DL), reinforcement learning (RL), among other techniques, are essential to promote the control of AVs and formulate safer and more socially optimized traffic policies, within an evolutionary learning process.

By understanding the main mechanisms surrounding the topic of AI applied to AVs, it was observed that the joint use of DL and RL showed promise in the field of autonomous driving, as well as the application of KANs network models to the detriment of MLP networks in certain learning contexts, although KANs are generally slower than MLPs with regard to training the models. given the same number of parameters.

Autonomous driving not only surpasses traditional traffic patterns, but also promotes more safety and comfort for passengers in stochastic and highly variable traffic environments, a fact that explains the growing increase in research in the area of autonomous vehicle driving, with AI as one of the main objects of studies in the area. Therefore, continuous research and innovation in this area is essential to address the challenges and maximize the benefits of autonomous vehicles in modern society.

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