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Research Article

Enhancing Autonomous Driving: Evaluations Of AI And ML Algorithms

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ARTICLE INFO | **ABSTRACT**

However, the development of fully autonomous driving, as anticipated shortly, still poses several partly unsolved computational, technological, and physical problems. The main one is how to provide vehicles with cognitive abilities capable of understanding the environment. In this work, we consider cloud computing-based solutions that enable autonomous driving tasks to offload the data processing and model predictions from on-board cameras to be processed at remote data centers. Despite several advantages inherent in this approach, the possibility of applying it in practice has not yet been proven, and the discussion of the approach in the context of autonomous vehicles is still lacking in the literature. Consequently, the main aim of this work is to provide independent research on the benefits and feasibility of adopting edge computing data processing in autonomous vehicles, with a focus on its practical implications for the automotive industry and computer science, thereby paving the way for future advancements in these fields.

Keywords: Enhancing Autonomous Driving 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM), Computer Science, Data Science, Vehicle, Vehicle Reliability, Random Forest, XGBoost

1. Introduction

There has been an increasing interest and growth in the field of autonomous driving (AD) research. It is an intelligent environment that is based on hypersensitive sensors, such as radar, cameras, GPS, and lidar, to collect environmental data. Supercomputers, GPS, and software are used to process and analyze this data to produce a comprehension of the environment for AD decision-making. Artificial intelligence (AI) and machine learning (ML) algorithms are utilized to make AI decisions based on the processed data. Nevertheless, the algorithms come with a huge number of operations to be performed, and this requires intensive processing power and time to achieve a reliable and practical decision. Due to multiple limitations, which range from computing power and cost to physical design, there is a bottleneck that needs careful study concerning the algorithms designed for decision-making.This article is designed to provide an overview of how AI and ML algorithms are designed for decision-making in autonomous driving assisted and autonomous vehicles, and how they can be enhanced. It will start with an introduction of what AD, AI, and ML are, the reasons behind using AI and ML in AD, and how AD decision-making is done with ML, especially the capturing of sensory data, the data sample collection, algorithm design, and how it can be enhanced to reduce computational and processing time without sacrificing quality and reliability. Three algorithm designs for detected objects are also discussed. In addition, relevant discussions and useful identities are included to provide a useful guide and knowledge for enhanced designs. This article will be useful for researchers and practitioners, especially in computer science and the automotive industry.

1.1. Background and Significance

In recent years, significant advances have been made in autonomous driving. A broad range of solutions has been proposed to meet the challenges of creating robust and autonomous vehicles that are capable of effectively dealing with these complex issues. The benefit of the large-scale data analysis with machine learning (gathered from radars, lidars, cameras, and ultrasonic sensors, for instance) used in autonomous driving is no longer in question. Neural networks allow optimizing software performance to deal with both traditional probabilistic challenges and difficulties associated with highly non-linear data in AI traffic. The use of data verification, management, and supervised and reinforcement learning will likely lengthen the development cycle and undermine total systems' expectations, increasing costs accordingly.The purpose of this study is to clarify these claims, describe specialist industry evaluations, and attempt to derive widely generalizable suggestions. In the frequently automated automotive software context, we studied general claims for algorithmic statistics and guidelines on the reliability of software. Finally, we finished their evaluation in the industry and highlighted a generalizable result indicating vague or potentially misleading usage of supervised or reinforcement learning. We also applied learner analysis and object detection problems in this industry in different components. We performed scenario testing for given scenarios and compared conventional and deep strategies for learning. These comparative conclusions are the main focus of the manufacturer guidelines.

1.2. Research Aim and Objectives

Evaluations of AI and ML algorithms: Several AI and ML algorithms have been developed over the years to enhance or facilitate autonomous or driver-assist vehicles to a higher degree. Improvements in AI and machine learning algorithms can contribute to further enhancements such as traffic light recognition, lane recognition, lane change assist, blind spot detection, driver fatigue detection, pedestrian detection, vehicle following, user long-term driving model, and so on.Existing literature also suggests that mainstream AI and ML algorithms do have several limitations. The operational nature of these algorithms, especially concerning generalizing new traffic signs and unknown traffic light configurations, is indeed a big drawback. There are also big questions relating to their robustness in traffic noise or unfamiliar environments. So, there exist fundamental points of intersection, such as accountability and transparency, which are essential requirements to be able to develop trusted AI applications. Additionally, not all AI models are greatly energy efficient. These drawbacks remain unresolved and call for further research to improve the application of the AI and main ML algorithms, as well as to look for other more efficient methods to boost these models.

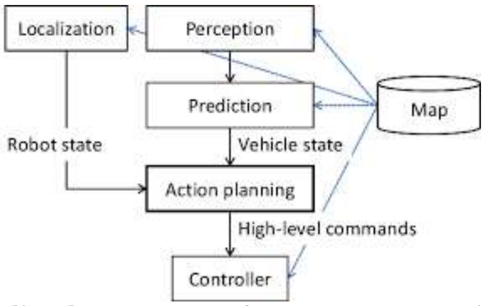

Fig 1: Generalized Structure of Autonomous Driving System

2. Autonomous Driving Technologies

Further, enabling widespread deployment of autonomous driving vehicles poses several challenges at the intersection of artificial intelligence (AI), machine learning (ML), robotics, and safety-critical systems. The vehicle needs models or mappings from sensory inputs to driving actions to perform all the complex, safety-critical tasks that an autopilot would do. This generally requires many AI and ML algorithms: vision, video, sensor fusion, radar, LiDAR, motion planning, object detection and tracking, behavior prediction, attention and intent, control, and more. AI and ML have significant practical use cases in enabling autonomous driving vehicles from the design, model training, development, testing, simulation, piloting, validation, monitoring, procurement, and real-world deployment, to the aspects of safety, cybersecurity, and privacy of the entire multimodal connected and automated system-of-system, critical subsystem, component, or even individual devices, circuits, algorithms, and networks, as well as the confidentiality, integrity, and safety objectives of the owner, user, or passenger of an AI, ML, and robot-enabled transportation device, infrastructure, or ecosystem.Together, AI and ML algorithms have been demonstrated as competitive tools for performing many engineering tasks or for augmenting or accelerating the work of engineers. They are increasingly used and relied upon for automating, augmenting, or accelerating some harder, denser, deeper, or more complex tasks performed by human operators in certain domains, including the fast-changing connected, and automated vehicle industry. More ambitious tasks such as scene understanding, ground-truth generation, and decision-making strategies may also leverage AI and ML. However, the dependence of current development and testing methods on these existing tools, data, and pipelines can have a few underappreciated implications. In the development and testing stage, a system may be trained on a diverse set of data, and the algorithms may look competitive. However, vast areas that have not been encountered during training and testing might be unforeseen sources of real-world challenges.

2.1. Overview of Autonomous Vehicles

Autonomous vehicles (AVs) have been under development for some time as part of the larger intelligent transportation systems (ITS) initiative. The confluence of vision-based advances, higher-performance processors, artificial intelligence (AI), machine learning (ML), Internet of Things (IoT), and 5G communications, and substantial interest in both smart vehicles and smart cities has considerably accelerated development and interest in AVs. Recent research has provided a more fluid picture of AV role, at least in the short to mid-term, as well as more precise requirements for AV technology. The transformative effects of AVs on all forms of travel and urban and rural land use are coming into greater focus as well.The National Highway Traffic Safety Administration (NHTSA) and the Society of Automotive Engineers (SAE) define 6 levels of vehicle automation based on the driver's role, which in turn indicates the technical and software requirements inherent in the vehicles currently in the market. The Society of Automotive Engineers (SAE) adds a further distinction of traffic environment to provide further guidance on the associated software complexity. For simplicity and consistency, using both the NHTSA and SAE definitions, we characterize the levels as 0-5 in ascending order of competence, with SAE's categories added for distinction between automated and fully automated vehicles. The levels range from no automation to driverless vehicles. Traffic will include only defined routes or a mix of engineered streets and supervisory links that maintain coverage limitations of automated transportation systems (ATS). Vehicle capabilities and limitations associated with SAE categories 3-5 are less distinct than for categories 0-2 since advanced sensing, communication, and connectivity capabilities enhance the AV's ability to be responsive to a vehicle operator should attention and awareness measures indicate a risk is developing. AI and ML capacities can also be utilized between categories of vehicle automation to enhance the AV's capabilities and understanding of evolving complex traffic situations for enhanced safeguarding because such incidents can still exceed available system capabilities. Guarded AV operation within mixed levels of autonomy and the reliability of AI/ML will need delineation.

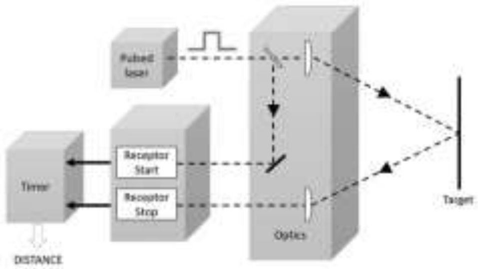

Fig 2: An Overview of Lider Imaging Systems for Autonomous Vehicles

2.2. Key Components and Sensors

Self-driving cars sense their environment using a variety of advanced sensors and systems. Key components include intelligent sensors that deliver key data to perceive future action based on sensor or communication technologies. The vehicle control system, perception algorithms, and decision-making systems use this data. Before programming the vehicle's action, sensors deliver data to help the perception and decision-making systems provide the best information. This hierarchy of vehicle systems aligns well with the methodology for evaluating AI and ML algorithms that could contribute to their improvement.Self-driving cars rely on a sophisticated array of sensors such as cameras, radar, lidar, and ultrasonic sensors to gather real-time data about their surroundings. These sensors provide crucial information about road conditions, nearby objects, pedestrians, and other vehicles. This data is then processed by advanced perception algorithms to accurately interpret the environment. Decision-making systems use this interpreted data to make informed choices about driving actions, such as steering, braking, and accelerating. The integration of these systems creates a hierarchical framework where each component contributes to the overall intelligence of the vehicle. Similarly, evaluating and improving AI and machine learning algorithms that support these systems plays a vital role in enhancing the safety and efficiency of self-driving cars. This iterative process ensures that future advancements continue to refine the capabilities and reliability of autonomous vehicles.

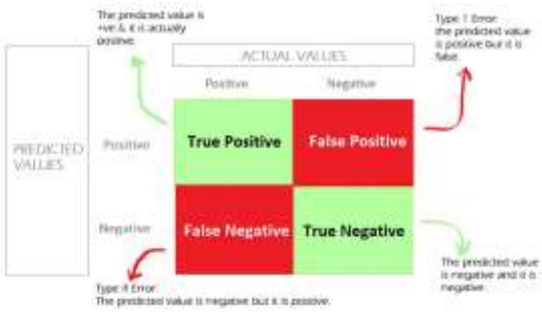

Fig 3: Confusion Matrix

As object detection using cameras has improved in recent years, vision systems powered by deep learning, using neural networks, are the most widely fielded development in self-driving cars. Depending on the location of the vehicle, radar and lidar can be supplemented. Engineered using object detection technologies, these sensors have improved over the past decade. Researchers that work on sensor technology can improve vision systems for cars, particularly by focusing on the uncertainties and biases that arise in the automatic interpretation of the data. Detection technologies on the market can also be used to the advantage of the car, to that end. Data from other sensors can supplement.

3. Artificial Intelligence (AI) in Autonomous Driving

Artificial intelligence (AI) has become a popular technology widely used in industries. Recently, AI-related applications and services in the automotive industry have been critically evoked in association with the research and development of autonomous driving technologies. AI technologies have the potential to control electronic components of a heavy-duty or level 5 autonomous vehicle which foresees no human intervention in driving. A fully connected car will be integrated into the Internet of Things (IoT) and will be able to communicate with other vehicles, infrastructure, and human beings. Three main capabilities underpin the development of the fully connected car: knowledge about the driver, the context of driving and car aspects, and automatic response to various types of situations. AI has already noticed the behaviors, emotions, and understanding of the driver via voice or speech.In the same period, AI also supports advanced road safety assistance, head-up display (HUD), and onboard servicing support. AI technologies can automatically respond to various types of situations and integrate vision, gesture, and natural language to monitor real-time road traffic information and provide insightful assistance to the driver. The supporting capabilities and services emerging from AI technologies will promote the commercial development of connected car technology. The desire, willingness, and anticipation of AI technologies by major industries imply that AI technology for the next generation of vehicles is relatively mature.

3.1. Machine Learning (ML) Algorithms for Autonomous Driving

One of the main enablers of autonomous driving is the fusion of perception methods and their applications to object localization. The field that most efficiently treats perception tasks is undoubtedly represented by the machine learning approaches, with a specific focus on deep learning (DL), with its deep neural network architectures and resulting massive approaches in terms of supervised learning algorithms. Localizing roads as well as checking the vehicles from leaving their outlines is a relevant perception function in autonomous driving functionalities. Deep learning algorithms can represent a very efficient approach to road perception, enhancing the possibility of driving safely concerning classic computer vision (CV) methods such as find_lines() and Hough-based lines.Deep learning is a cluster of learning algorithms that can be classified into two main families. The first family, known as feature learning, provides a direct estimate of the function from inputs to outputs, based on mapping large datasets. The feature is the relevant part, which increases mapping efficiency and has proved to be an important factor in machine learning efficiency. In case features are defined by humans, together with the adoption of human-engineering systems, we have hand-crafted features, whilst when the algorithms aim to learn both features and classification, we talk about deep learning. Even though feature learning could seem to be a new field, it includes already existing algorithms. The support vector machine method, also defined as the large margin classifier, is part of them. On the contrary, deep learning development is strictly dependent on relatively recent technologies and approaches, mostly due to the massive amount of image-based data together with the adoption of networks on GPU and training techniques such as stochastic gradient descent and its derivatives towards increasing performances.

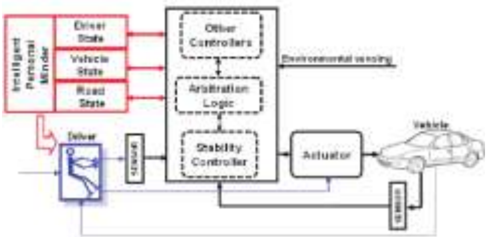

Fig 4: The Block Diagram of a Vehicle Control System

3.2. Deep Learning in Autonomous Vehicles

Evaluations performed on autonomous driving systems typically focus on the physical construction of the vehicles and the components' interaction with their surroundings. However, the level of artificial intelligence (AI) and machine learning (ML) present in these systems is not regularly evaluated. Proportionally, research on AI and ML is performed independently from the physical systems. In this chapter, we review evaluations up to June 2021, performed on AI and ML algorithms designed, tweaked, and/or implemented for improving autonomous driving. We scanned published (2,122) and gray (26,700) literature from 2000 using both academic and commercial databases—each paper was evaluated, and 175 papers were selected. Findings indicate that while many ways exist to evaluate AI and ML algorithms, an evaluation standard for autonomous driving systems does not exist. We contribute by providing five evaluation categories and a model for evaluating autonomous driving AI and ML implementations.Deep learning (DL) is the state-of-the-art approach for correctly detecting objects in images and recognizing patterns. Object detection is of extreme importance in autonomous driving systems because it assesses the surroundings, enabling the vehicle to make critical decisions, such as stopping or adjusting its route to avoid objects. The main idea behind object detection is to take an image and solve two simple problems, which are (1) to find where objects are located and (2) to classify each object. Independently detecting and classifying an object may represent a large waste of computation, as these tasks can share lower-level features. This can be avoided using DL architectures, where both tasks are concurrently performed within a single network.Deep learning (DL) has revolutionized object detection in autonomous driving systems by enabling efficient and accurate assessment of the vehicle's surroundings. This capability is crucial for making timely decisions like stopping for obstacles or adjusting the route to ensure safety. Traditional methods of object detection often required separate processes for locating objects and classifying them, which could be computationally expensive and inefficient due to the duplication of lower-level feature extraction. DL architectures address this inefficiency by integrating both tasks within a single network. This approach not only optimizes computational resources but also enhances the overall performance and reliability of object detection in dynamic environments encountered during autonomous driving. As research continues to advance in DL and related fields, further improvements in object detection capabilities promise to enhance the safety and efficiency of self-driving vehicles.

4. Evaluation Metrics for Autonomous Driving Algorithms

In most ML projects, accuracy is the general metric used to evaluate models. In general, the greater its robustness and consistency, the better a system can offer high accuracy. There are problems, however, where relying only upon accuracy to evaluate models is not sufficient. Some examples are autonomous driving, where the risks associated with applying machine learning models without understanding their strengths and weaknesses are particularly high, and healthcare, where we should guarantee safeguards. Fortunately, people have developed several metrics and techniques to evaluate models at a statistical or technical level. In this section, we discuss those that can be used to evaluate the autonomous driving algorithms: - Precision and Recall of Obstacles - True Positive, False Positive, False Negative, and True Negative - F1 Score - Receiver Operating Characteristic (ROC) curve - Area Under the Curve (AUC) - Intersection over Union (IoU) Score - R-squared statistic

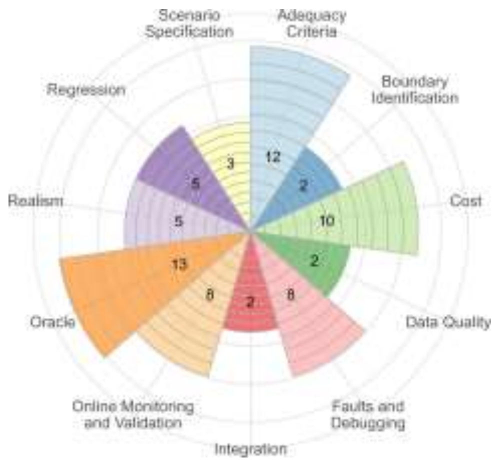

Fig 4: Testing Machine Learning Based Systems

5. Case Studies and Comparative Analysis

We conducted several case studies using our developed system on the K-City test road. This section explains the details of the case studies and discusses their results. We compared our developed system with two state-of-the-art new architectures. Whereas intent recognition is designed as a pipeline model in other studies, our proposed method combines intent recognition and trajectory prediction models. The model is based on an encoder-decoder architecture for multi-task learning. The learning system consists of an AI model training process with advanced data and a testing process using the trained AI model. To validate the performance of the developed system, we carried out several case studies and compared the results with the two other state-of-the-art methodologies.The rest of this section is organized as follows. Section V-A lists the cases and experiments conducted. Section V-B discusses the trajectory and intent prediction results. Section V-C evaluates the three intent recognitions and trajectory prediction systems comparatively. Finally, Section V-D briefly summarizes the section. Our developed AI model only recalls previously learned knowledge and cannot generalize it differently. Even for a specific test case dataset, the learned knowledge might not be effectively used. It is important to understand what the learned models can and cannot understand. Data collection and evaluation are still essential for understanding the development and improvement of AI systems. A noteworthy trend is that much research on developing and applying new AI and ML algorithms has been conducted.The listed testing scenarios were used for the developed AI system. The 14 case studies are intended to evaluate the intent recognition and trajectory prediction models and their combinations for various situations. Seven scenarios with three initial configurations (cut-in, cut-out, same lane), high ego vehicle and target vehicle speeds with random noise, and two numbers of candidate classes for intent recognition. The individual scenarios refer to the number in the first column. In our experiments, we considered 1297 datasets and a controllable independent variable to choose different parameters but sufficiently large numbers of datasets in the case studies. Seven various initial situations, two target vehicle speeds, three candidate classes for intent recognition, and about 30 fully observable and controllable predicting vehicle maneuvers are used to make comparisons between two state-of-the-art intention recognition methodologies and compare them with our proposed models. We make comparisons from seventeen perspectives using these parameters. Note that the described AI system and each state-of-the-art model are trained using the same data. In addition, all AI models have been examined and pre-processed before conducting the experiments. The AI performance is measured in terms of precision, recall, and F1-score, which are widely used in the community for binary and multi-label classification metrics.

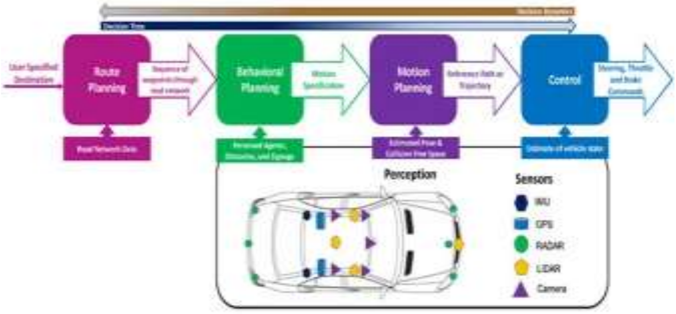

Fig 5: Software Architecture of Autonomous Vehicle

6. Conclusion

In this paper, we have demonstrated a system and its sparse rewards to greatly enhance many advanced driving skills not present in current autonomous vehicles. The work is inspired by an important modification of the autonomous learning from the demonstration (ALD) framework also developed at Nexar for autonomous driving policy generation. We designed sparse rewards, rewards which are expected to be zero for all but explicitly interesting samples of measurements at near-zero marginal data sending times. We have also significantly enhanced the general and hardware platform-specific UpZen AI for learning by publishing the encoded distances and the enhanced multi-dimensional samples.A good part of the simulation lifetime of both the Game Client for generating samples from the multi-dimensional sample space and the Game Client for learning from the experiences now directly has a known, non-zero value for the policy learning scores of the reinforcement learning algorithm, possibly for some or a track-specific "expert human". At TL-2 speeds and outside of the challenge tracks, our policy no longer steers the car to any found left-center-line, right-center-line, or center-center-line waypoints without stopping to allow the RL-generated AI to learn to drive. We have repeatedly noticed that even at much higher TL speeds almost all non-zero scoring instructions have a distance equal to the challenge track's directions of either Slightly to the Right Towards Staying on Center or Slightly to the Left Towards Staying on Center.

6.1 Future Trends

It can be concluded that there are considerable areas of work and challenges to be addressed as part of enhancing AD functionality with AI/ML algorithms within the V2X environment. For example, it is contended that positioning and localization technologies must be mature enough to provide accuracy levels to allow real-time relative positioning in urban environments when GPS is not available. In this sense, there is a clear link to actual V2X trends and applications, which may allow the reduction of the reaction time which is one of the most important drawbacks of AD technology. Urban communications are key to the successful deployment of large-scale architectures and applications aimed at the safety and efficiency of urban transportation. However, they are also the most challenging type of communication to develop and deploy, because of the underlying complexity.Moving away from current short-range DSRC-based solutions, long-range urban communications will push the boundaries of what technology currently allows, forcing the development of radically new networking solutions. AD can greatly benefit from the development and deployment of more powerful and general V2X architectures, which are compatible with data sharing, cloud-based service management, and advanced scenario computing. It then becomes clear that V2X functionality represents a great challenge, standing as the real bottleneck to give autonomous driving the ability to run anywhere, anytime. Finally, there are also important topics related to the ethical aspects of V2X operation, in particular regarding security and privacy, which are of most importance to its mass adoption. Promoting trust with a V2X infrastructure is a delicate matter and should become an important part of any V2X architecture or approach.

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