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Enhancing Autonomous And Battery Electric Vehicle Performance Using AI And ML Algorithms

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ABSTRACT

The document outlines a comprehensive analysis of testing scenarios conducted to evaluate an AI system's intent recognition and trajectory prediction models. Utilizing 14 case studies, various scenarios were designed to assess the performance of the models in different situations. These scenarios involved multiple initial configurations, speeds of ego and target vehicles, candidate classes for intent recognition, and vehicle maneuvers. The experimentation was based on a significant dataset to explore the parameters thoroughly and compare the proposed models with existing methodologies. Precision, recall, and F1-score metrics were employed to measure the AI system's performance accurately. The paper also highlights the importance of training the AI models with similar data and subjecting them to pre-processing before experimentation. The study culminates in a comparison of the developed system with state-of-the-art architectures, emphasizing the novelty of combining intent recognition and trajectory prediction models for enhanced performance. Additionally, the work carried out in this article references the research of Mandala and Srinivas Dolu Surabhi et.al, emphasizing the benefits of their hybrid machine-learning model for predictive maintenance in passenger vehicles, specifically focusing on the proposed hybrid model's accuracy and potential to revolutionize predictive maintenance frameworks in the automotive industry.

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

1. Introduction

There has been an increasing interest and growth in the field of autonomous driving (AD) and battery electric vehicle (BEV) research [1], [2], [3]. 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 [4], [5]. 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 the domains of both computer science and the automotive industry.

1.1. Background and Significance

In recent years, significant advances have been made in autonomous driving [7]. 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 [8], [10]. The use of data verification, management, and supervised and reinforcement learning [9], [13] 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 [15], [16],]17]. 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 focus of the manufacturer guidelines. One area that we can leverage AI, ML in BEV vehicles is in estimating the battery state of health (SOH) which is an important area to focus for electric vehicles (EVs) as it directly influences the performance, safety, and cost-effectiveness of both the battery and the vehicle. Accurate SOH estimation allows EV owners to assess the reliability, range, and performance of their vehicles. It also aids buyers and sellers of used EVs in accurately valuing the product, boosting confidence in the EV's worth, longevity, and range. Moreover, it helps determine whether a retired EV’s battery is suitable for reuse and repurposing or should be sent directly to recycling.

Predicting SOH under dynamic conditions is particularly challenging due to the complex and nonlinear interactions between battery parameters and the operating environment. These interactions can vary significantly based on driving patterns, charging strategies, and ambient temperatures. Such factors influence the electrochemical and thermal processes within the battery, leading to diverse aging mechanisms and degradation rates.

1.2. Related work

In this section, we will focus on reviewing the recent methods and challenges of using data-driven techniques, such as machine learning, deep learning and digital twin, to estimate and optimize the battery design which is important for Autonomous vehicles.

In the operational framework [18], [20] the Autoregressive (AR) model utilizes battery voltage and current data to estimate the SOH. Leveraging its capability to capture temporal dependencies, the AR model analyzes historical information, discerning trends indicative of the battery’s health. The Relevance Vector Machine (RVM) complements the AR model, crucially enhancing SOH estimation accuracy. The RVM’s primary role is to address errors in the AR model’s output compared to the actual SOH value, refining overall precision. This compensation involves dynamic adjustments to weights and relevance vectors, optimizing agreement between the modeled and actual SOH through an adaptive learning process, ultimately contributing to a more reliable battery health estimation. The methodology employed in [19], [20], [21] integrates the Two-Step Noise Reduction Method, Domain-Specific Features, and Stacking Ensemble Learning. The Two-Step Noise Reduction Method employed in this study utilizes a moving average filter and a wavelet transform to effectively reduce noise present in the battery data. This method aims to enhance the overall data quality by mitigating disturbances and inconsistencies. Additionally, the methodology incorporates Domain-Specific Features, a set of characteristics derived from domain knowledge and battery physics. Examples of these features include discharge time, discharge energy, and discharge capacity, providing valuable insights into the battery’s behavior and performance. Lastly, the approach integrates Stacking Ensemble Learning such as linear regression, support vector regression, and random forest regression into a meta-learner. This ensemble learning strategy contributes to improved prediction accuracy and generalization by leveraging the diverse strengths of individual models. The combination of these methods forms a comprehensive approach to battery data analysis, addressing noise reduction, feature engineering, and predictive modeling within a unified framework. Careful consideration is required in terms of model evaluation due to complexity and computational resource requirements.

The approach provided by authors [7], [8] delves into the utilization of machine learning algorithms for predictive maintenance in passenger vehicles, emphasizing the significance of engine telemetry data and the challenges associated with algorithm convergence due to infrequent component failures. By proposing a directed study involving simulated failure events and continuous online monitoring of engine status, the research advocates for improved predictive maintenance solutions. Additionally, the exploration of IoT technology layers' efficiency and cybersecurity threats highlights the need for resilient machine learning algorithms in the face of potential data injection attacks. The study concludes with the successful implementation of a hybrid machine-learning model for accurate time-to-failure predictions, paving the way for a more comprehensive predictive maintenance framework and demonstrating the impactful role of machine learning technology in the automotive industry's evolution.

The proposed research method by Mandala and Srinivas Dolu Surabhi et.al in papers, [7] & [8] offers unique advantages in the field of predictive maintenance for passenger vehicles using machine learning algorithms. These include the development of a hybrid model with over 98% accuracy for predicting time to failure, the possibility of creating a comprehensive predictive maintenance framework beyond a single algorithm, and the potential impact of machine learning technology on the industry. Furthermore, the research done by Mandala et.al to address specific challenges in maintenance tasks, explore opportunities for improvement, and verify the framework through a practical case study. Additionally, the study highlights the importance of feature engineering, model evaluation, and considering the effectiveness of various layers of IoT technology for predictive maintenance in future research endeavors.

1.3. Research Objective and Methodology

In this paper, we discuss a methodology for enhancing the performance of Autonomous and Battery Electric Vehicles (BEV) based on predictive maintenance using machine learning algorithms proposed in the articles, [7] & [8]. By leveraging insights from predictive maintenance, autonomous vehicles can proactively address potential issues, ensuring optimal performance and safety on the roads. We have developed a new machine learning algorithm based on time-series data analysis, employing Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. These models excel in processing and learning from sequences of data, making them ideal for managing the continuous data streams generated by these vehicles. For instance, RNNs and LSTMs can monitor and predict the health of vehicle components such as batteries and engines by tracking performance metrics over time. This capability helps preempt potential failures, reducing downtime and maintenance costs. Furthermore, these networks can optimize vehicle performance by analyzing historical telemetry data, including speed, acceleration, battery usage, and environmental factors, making real-time adjustments to improve efficiency and extend battery life.

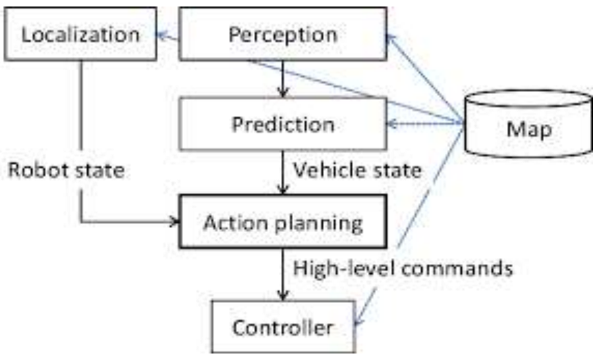

Fig 1: Generalized Structure of Autonomous Driving System

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 [15], [16] 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 [10], radar, LiDAR [20], motion planning, object detection and tracking [29], 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 [21], [22], 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 [13]. 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[16], [17]. 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.

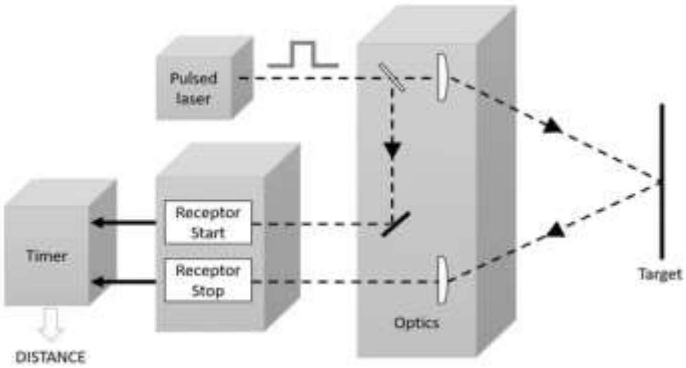

Fig 2: An Overview of Lider Imaging Systems for Autonomous Vehicles

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.

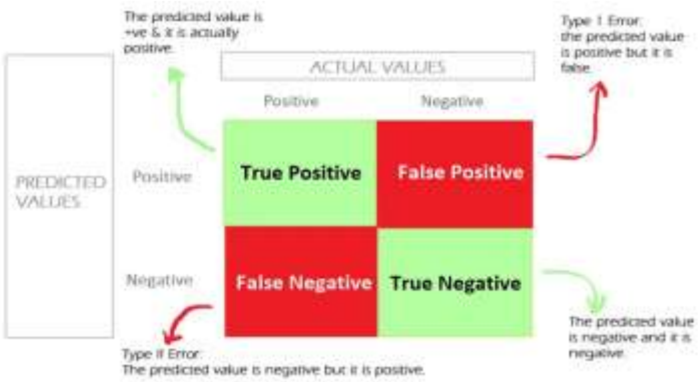

Fig 3: Confusion Matrix

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.

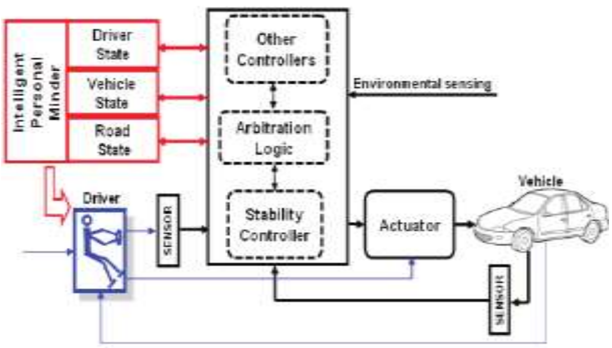

Fig 4: The Block Diagram of a Vehicle Control System

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.

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

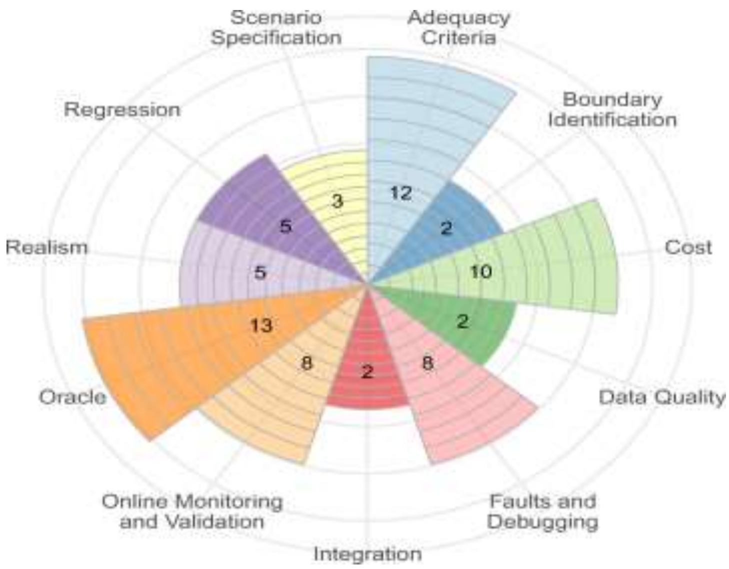

Fig 4: Testing Machine Learning Based Systems

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.

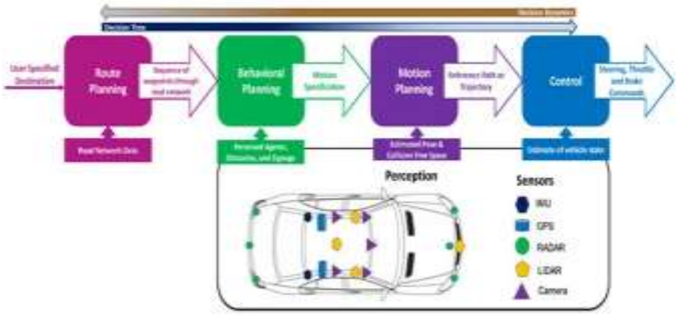

Fig 5: Software Architecture of Autonomous Vehicle

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, caused 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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