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Vehicle Control Systems: Integrating Edge AI and ML for Enhanced Safety and Performance

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Abstract
AI-driven dynamic trajectory planning and control systems are the keys to enhancing safety and performance for the next generation of autonomous vehicles. The growing demand for autonomous vehicles is pushing relevant companies to deploy the latest AI/ML methods to build better, more reliable, and versatile control systems. Current software architectures supporting the deployment and execution of AI in vehicles rely on centralized or decentralized control. Centralized approaches optimize performance over specific tasks, but they are poorly scalable. Decentralized approaches target scalability but struggle to maximize global efficiency and safety, especially when handling the variability and unpredictability associated with real-world scenarios. In this talk, we bring on the discussion that modular software architectures offer a more appealing way to organize the three core functions of future autonomous vehicles, i.e., sensing, planning, and control.Moreover, fostering the debate and collaboration between companies, academic institutions, and community-driven open-source foundations is a key priority to increase the number of potential solutions from a vast array of currently applicable technologies such as Deep Reinforcement Learning, Model Predictive Control, and Motion Planning Field, to name a few. The scale needed for a production-worthy solution is not achievable by any single company. Finally, an increasing level of democratization and standardization has a desirable side effect for the community itself: making the final user confident in the performance and safety of AI-driven products is the key to unlocking the adoption of fully autonomous vehicles.

Keywords: Vehicle Control Systems: Integrating Edge AI and ML, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliability

1. Introduction

It is estimated that less than 20% of the total cost of owning an automobile over its expected use life is in the purchase price. The remaining 80% is spent on operations, maintenance, and repairs. One approach that might be taken to reduce that 80% cost is through the development of vehicle control systems incorporating edge artificial intelligence (AI) and machine learning (ML) for enhanced performance and safety. These edge hardware and software developments are intended to work in tandem with, rather than replace, the computing and signal processing capabilities of the software-based engine control unit (ECU) that already exists in every car.This paper begins with an overview of existing vehicle control systems. The fundamental issues related to edge 'embedded' AI/ML acceleration, technologies to address these issues, and recent developments and applications to commercial vehicles are then outlined. These are followed by avionics industry experiences and recent industry-specific hardware developments in machine learning. They are being applied to vehicles as well. The paper concludes with embedded AI function enhancement and systems integration issues that serve as both industry and applicable government policy planks. Such planks support and encourage the widespread utilization of edge artificial intelligence devices in customer-owned automobiles serving multiple purposes.Drawing insights from experiences in the avionics industry, the paper examines recent developments in hardware designed for machine learning applications and their adaptation for automotive use. These developments are crucial as they pave the way for embedding AI functionalities directly into vehicles, thereby enhancing operational efficiency and safety.

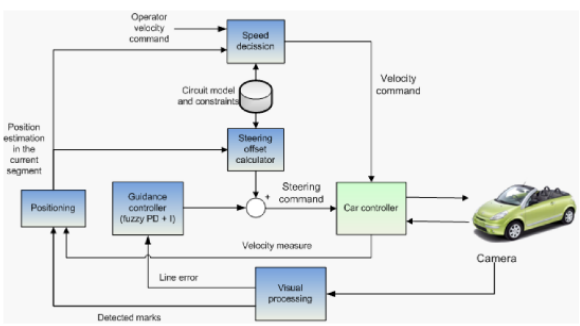

Fig :1: Full system architecture

1.1. Background and Significance

Automated vehicle control systems have emerged as the means to boost operational and performance metrics for a variety of vehicles such as cars, trucks, and unmanned aerial vehicles. Autonomous vehicles are used to improve traffic throughputs within cities, reduce energy consumption associated with propulsion systems, and increase safety by reducing human errors. This has been enabled by a drastic drop in the costs of sensors and communication technologies, which has fueled the generation and voluminous influx of different types of data.

For autonomy to become widespread, we must go beyond the level of creating models a priori of driving scenarios with fixed rules of engagement by integrating new data as it becomes available in the form of reinforcement learning or deep learning models. These models must take advantage of the consolidation of resources at the edge, which, through federated learning, can help aggregate experiences across a variety of use cases for a potentially large number of autonomous vehicles on the road to stay current with the changes in dynamically driving scenarios.

This presentation aims to summarize the current state of vehicle control systems and the steps leading to the widespread deployment of edge AI for enhancing the safety and performance of these complex systems.

1.2. Research Objective

As mentioned in the previous sections, the sharp intersection between statistical learning and control theory has developed a vast body of work in the fields of control, learning, and model inference. While this research has yielded various theoretical tools and computational methods and provided a better understanding of the tighter integration of statistical learning and control, the advances, especially at the intersection of ML, AI, and traditional AEC, have remained largely competent.On the one hand, most of the prior work has focused on the constrained form of operation and power of traditional deterministic control systems. This has limited the broader application and evaluation of AI and ML algorithms across many potential applications, especially where learning methods can achieve high proficiency. On the other hand, robustness is the key feature of traditional AI/ML research. However, under the operating constraints or disturbances of control systems, it is difficult to maintain system performance levels. Therefore, the integration of AI, ML, and control theory in the vast number of AEC engineering applications is still in its infancy. Moreover, most of the successful results and rich integrations have been developed in function-specific areas using a wide variety of ad-hoc technologies without much regard for the richer ideas and more systematic perspectives afforded by others.

2. Fundamentals of Vehicle Control Systems

Vehicle Control Systems: Integrating Edge AI and ML for Enhanced Safety and Performance2.1. Closed-Loop Control Closed-loop control plays a key role in vehicle systems. The fundamental control problem is to determine the system input (command) that ensures that the state of the system follows a desirable trajectory or evolves within a desired region of the state space, even in the presence of uncertainty. The desired or reference state trajectory is generated by some automated planning system or operator input. Closed-loop control can be physical (such as the power steering, throttle, and brake in a modern vehicle) or cyber-physical, where the physical actuation is modulated by a controller capable of reasoning about system dynamics, the effect of actuation and sensor noise, as well as estimating the current state in real-time.2.2. Vehicle Models Vehicles are often modeled using point mass models, which represent vehicles as point masses equipped with speed and steering angle actuators and translational and angular dynamics. For certain control problems, linear or Nonlinear Advanced Vehicle Models (NVEMs) are used. For automated planning problems, the vehicle is modeled as an autonomous hybrid model, where the continuous dynamics are described by the NVEM, and the discrete state transitions are defined by the stacked rectangles and other non-smooth constraints such as brush tires and road/wheel contact models. Some specific control systems are modular, and modular models can be derived from NVEMs. The high-level behavior of these vehicles can be formulated as control problems over a finite state space and solved using methods such as POMDPs.

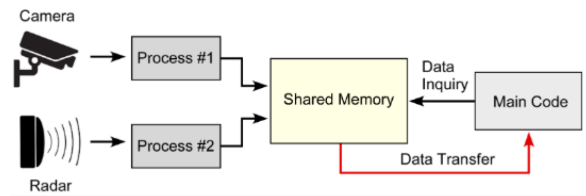

Fig :2: Approach for mitigating network latency using shared memory to store multiple sensor data

2.1. Basic Components and Functions

Ike enables control of the velocity; hence vehicle acceleration and deceleration in speed frames. The yaw rate and both lateral acceleration measurements control the curvature while the forward acceleration controls the speed. The triple integral in the integrated version of the system made it robust against the longitudinal evolutions in lateral acceleration signals often causing instability in conventional systems. The combined velocities of the two above functions produce roll- and pitch-reference angular velocities of the vehicle. In conjunction with the damped characteristic of the sideslip difference control allocation techniques, which provide linear and decoupled control of the inputs, are applied giving in particular negative roll input increasing the sideslip of the inner wheel.The brake pressure control is a command tracking loop that utilizes a linear feedback control structure based on the overall linearisation of the brake system. It preserves the decoupling behavior and produces pressure references for given front-and-rear axle brake effort balances. The traction system signal is veto provided by the state of the road friction estimation running in traction and stability feedback loops which correct the individual wheel velocity measured.

2.2. Challenges and Limitations

We can categorize challenges and limitations based on the model and application type. For model type, those challenges we faced using the deep learning model, such as it requires large labeled data, without labeled data, deep learning performance is going to reduce, and the interpretability of the model is difficult. Then for the application type, we faced challenges to define safety performance when clustering algorithms are used for building CDsP from the normal driving data. Moreover, we faced visible quality issues and observed reduced maximum throughput quality incorrectly controlled traffic-light bypass functionality that led to stops after the overlay was implemented on other routes. And deep learning can't define future probabilities, such as how many people need at least approximately zero point five years of age to use the seats with child-restraining elements? This is important to select the right vehicle and ensure safety. Then interpretation without validation data and the expert and end-user interpretation required by the insufficient validation data. This data is not always used during the model-building process, and overall, there is a need for a good balance between AI data and expert human knowledge for quality control applications.

3. Edge AI and ML Technologies

For automotive systems, edge computing has always been the critical implementation approach due to real-time vehicle response requirements to guarantee safety. From the safety design aspect, the application of open-source embedded machine learning toolkits has also been a commonly used approach for neural network design on edge computing platforms. With recent advancements in accelerator hardware as well as embedded machine learning libraries, applying reinforcement learning on edge computing platforms for optimized controller development can be an effective approach to utilize edge computing capabilities for improved performance.To support the enabling of the open-source reinforcement learning framework, the paper presents the reinforcement learning integrated state of charge management algorithm development within the easily accessible ROS2-based simulator open-source project. The reinforcement learning-based control design automated objective function formulation and hardware-in-loop generation process, solutions involving Python sci-kit-learn and ROS2 incorporated Williams sensorless PMSM motor control hardware are also described.As such, edge computing is now standard in all vehicle platforms for safety-related components. For many applications, especially for machine learning, the separation of embedded hardware resources allows model training and validation to be done on high-end computing infrastructures. After the model development phase, the AI model can be deployed to the edge with various software and hardware constraints available to minimize the processing delay and computational resources for live vehicle AI implementations and further process/vector capabilities. Deployed edge AI models can also provide extra features independent of traditional controls and provide authenticated safety improvement enhancements through vehicle communication networks.For vehicle control applications, safety-related edge AI functionalities need a real-time response as close as possible to vehicle controller performance, only making sense of enabling fast actuators and sensors for additional vehicle performance improvement provided by on-edge AI model-based optimization algorithms.

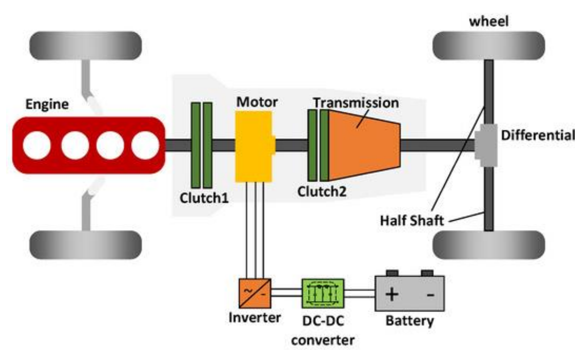

Fig :3 P2 hybrid vehicle structure

3.1. Overview and Definitions

We focus on a vehicle controller, that is, a set of control functions for a vehicle that drives the vehicle. Examples of vehicle controllers include path-following for automated driving or cycle-by-cycle torque control for energy management. The distinction between vehicle controllers and ECU controls can be subtle but important. Simply put, the ECU runs the vehicle but does not control vehicle operation, that is, setting a speed setpoint for a vehicle speed control if we consider the cruise control. Vehicle controllers, on the other hand, actively drive the vehicle to achieve some desired outcome.An important characteristic of a vehicle controller is that the input to the controller is some measure of the vehicle dynamics, while the output is a set of required system functions. Fuzzy logic, PID, and MPC controllers that manage vehicle systems such as anti-lock brakes, torque vectoring, and drive mode initiation based on tire slip angles are examples of vehicle controllers. Even the basic proportional and integral controllers associated with cruise control can be thought of as vehicle controllers.Behavior functions are AI and ML algorithms that define the control of these vehicle systems using vehicle dynamic inputs. The vehicle control function that computes tire friction characteristics using tire sensor inputs is an example of a behavior function. Running any vehicle dynamic model with the vehicle speed setpoint as input and computing the vehicle's path using lateral and longitudinal offsets from a lane model is also a behavior function. Traction control and torque vectoring strategies based entirely on vehicle dynamics inputs can similarly fall into a general category of behavior functions. Note how two different vehicle functions can be based on different kinds of AI and ML technologies (in this case, tire model tables vs. neural networks).

3.2. Applications in Automotive Industry

System-on-chip (SoC) technologies play an essential role in modern automotive computing systems. These technologies implement various automotive systems, including advanced driver assistance systems (ADAS) and the domain-controller approach. Within these systems, there is a need for greater functional safety (FuSa) and security to ensure data integrity, vehicle control, and personal safety. In this study, we explore the model application, software, and hardware aspects of an automotive computer exception management system (ACEMS) for an SoC to address these issues.In-vehicle driver assistance systems are becoming increasingly common in modern vehicles. Many SoC-based electronic control units (ECUs) enable feature-rich infotainment, telematics, and ADAS capabilities, improving vehicle safety. With these sophisticated features and capabilities, in-vehicle systems will generate more command and telemetry signals, increasing the number of ECUs and the complexity of automotive networks and nodes. However, with the increase in the number of ECUs, the requirements have to be raised to improve functional safety, particularly in extending the concept of reliable vehicle operation beyond FuSa (functional safety) and guaranteeing passenger safety and data integrity. This is increasingly salient as more vehicle control moves from drivers to increasingly sophisticated in-vehicle control systems leveraging edge artificial intelligence (AI).

4. Integration of Edge AI and ML in Vehicle Control Systems

Developing and deploying machine learning (ML) for intelligent vehicle control systems presents a myriad of challenges. Relevant data capture, labeling, and curation are required to efficiently train ML models to maintain predictively acceptable performance despite non-stationary and evolving environments. With the prospect of ML in vehicle controls, full stack development and deployments need to be explored, not only algorithmic model advancements. Edge AI now offers state-of-the-art modular sensor fusion and embedded ML AI accelerators. Edge AI mechanisms can generate high prediction accuracy for a latency and throughput budget even under limited resources. However, bringing edge AI models to live production systems requires many decisions regarding edge AI model architectures, ultra-efficient runtimes, cutting-edge annotation tools, and novel domain KL methods necessary to evolve model performance. These integration choices should align tightly with the development of supporting infrastructure and real-world data validation. The solutions must align well with regulation and ethical requirements.Deployment of traditional vehicle control systems presents substantial challenges associated with maintaining acceptable levels of vehicle and system safety while reliably managing the operation of the myriad mechanical, mechatronic, and electronically controlled components. Moreover, due to the continuous need to simultaneously manage vehicle operating conditions, edge and extreme environmental conditions, predict performance, and support system safety and security constraints, significant engineering effort must also be allocated to ensure robust and comprehensive risk and uncertainty models are developed, validated, deployed, and maintained. Effectively integrating edge AI technologies can make a huge difference in the development cost, and performance, and keep the development team focused on the technical development of the vehicle systems and supporting infrastructure evolution to thrive and preserve relevant capabilities. Key factors in deciding to leverage ML for control systems include the need for scalable operating systems, sensing modality that can support data-driven development, the ability of algorithms to manage the co-optimization of a plethora of inputs and outputs, need to auto-determine optimal decision-making, tracking, estimation, and control functions, need to develop datasets and scoring suitable for training and validation, and intent to leverage increasingly efficient computational hardware and data storage.Developing and deploying machine learning (ML) for intelligent vehicle control systems introduces a range of complex challenges that must be navigated effectively. Crucial among these are the processes of capturing, labeling, and curating relevant data to train ML models effectively. This is essential for ensuring consistent and predictive performance in dynamic and evolving environments typical of vehicle operations.ML's integration into vehicle control systems necessitates a holistic approach encompassing full-stack development and deployment considerations, beyond merely advancing algorithmic models. Edge AI technologies now offer sophisticated capabilities in modular sensor fusion and embedded ML AI accelerators. These advancements enable high prediction accuracy within constrained latency and throughput budgets, even with limited computational resources.

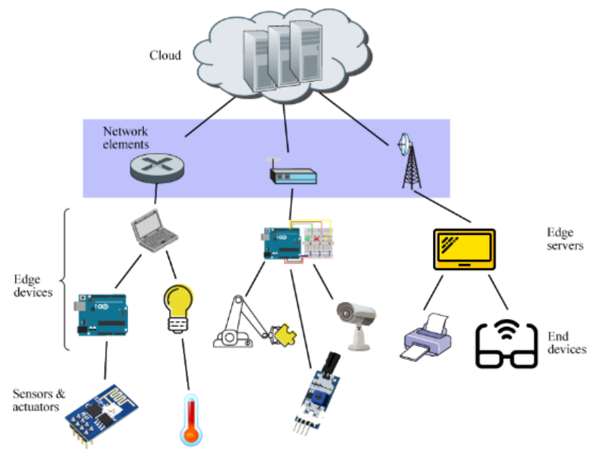

Fig :4: Schematic diagram for edge computing

4.1. Benefits and Advantages

Deployment of advanced driver assistance and autonomous vehicle features by using traditional embedded ML workflows and platforms could often result in sub-optimally trained models (due to the edge constraints related to cost, power, and thermal dissipation requirements), subjugation of edge safety and security considerations including functional safety (FuSa), ISO 26262 compliance, and security – to the overall model accuracy and task efficacy considerations. An erroneous adversarial interference with ADAS/autonomous vehicle decision-making functionality could result in disastrous consequences in the case of road-going vehicles; the safety and security concerns, especially concerning malicious adversarial attacks, exploitation, or 'fooling' of perception and control functionality have been very well documented. Consequently, the approach would often require large-scale latency-prone tests and validation, typically involving the execution of expensive simulation or over-the-air (OTA) update methodologies, to address a wide set of possible adversarial inputs.Concerns related to training, validating, and ensuring the safety of deployed ML models – inference – then become the bottlenecks in the implementation process. However, many of these concerns (related to adversarial input generation, verification of FuSa properties, safety and security of the inference data and the response) could be better addressed by leveraging comprehensive integration of applicable ML, AI training, validation, and inference frameworks with the deployed edge AI, edge ML lifecycle, and run-time control systems. While traditional defense-in-depth approaches could be invoked to address many of the aforementioned concerns, smarter edge model-training integration could provide significant performance, power, and cost advantages to the vehicle controller, especially with the rapidly evolving features of advanced driver assistance systems.

4.2. Challenges and Implementation Issues

In this section, we discuss the key challenges and implementation issues in the deployment of ML-based AI systems into vehicle ECUs. Here, the presentation is relatively high-level, avoiding the use of notation and detailed equations to make the work accessible to both control and AI communities. We can summarize key challenges in embracing AI/ML-based vehicle control systems without loss of generality as follows:

1. ML implementation for small, embedded control applications. ML-based methodologies are known to be computationally expensive and time-consuming, especially from a hardware design, verification, validation, and implementation standpoints. Even with adequate HIL and SIL validation mechanisms, safety concerns may keep such AI-infused applications out of critical and safety-critical applications, such as lane change execution and high-speed platooning. On the other hand, with the ability of high-capacity and high-performance mobile processors and sensor technology, cars are predicted to become HPC on wheels.

2. Real-time learning algorithms. ML-based algorithms tend to require a large amount of data, including live data, data uploaded from all connected sources, and duly processed data to extract as much valuable knowledge from. On the other hand, driving situations are ever-changing, with a vast number of live scenarios emerging. Apart from this issue, a successfully trained system may fail to work when deployed in a vehicle with nominal and off-nominal conditions. Furthermore, how to let models dynamically learn interesting and relevant new corner-case driving scenarios, unknown in the development data set, for the allowed model to enclose safe convex sets must be resolved for the industry to adopt the proposed technologies.

5. Case Studies and Examples

In this section, we describe a few vehicle control case studies and examples to illustrate the wide variety of problems that edge AI can address.Collision Avoidance: The classic vehicle control system that most people think of first is collision avoidance, and with good reason, as it is surprisingly effective! A key aspect of practically all collision avoidance systems is the steering control system, which determines how to steer out of the way of the impending collision. It's a stunning fact that less than 1 degree of steering (about a 1-inch turn of the steering wheel) could effectively minimize the impact and save human lives when there were no better alternatives, such as hitting the brakes. In many cases, crashing straight ahead into a tree that was deflected away from the driver's door rather than into the side of the car is better than avoiding it. Braking has a similar aspect, especially in urban areas, where the incursion of other vehicles into the intersection during the red light is a significant hazard.Driver Distraction and Impairment: Vehicle AI-oT systems can also improve safety by alerting drivers that they are distracted from safe operating. Substantial advancements in machines are poised to play a far stronger role in monitoring drivers virtually continuously, perhaps without being as intrusive to users as cameras since the system would be immediately disengaged if the driver's facial condition changed significantly and returned to normal in a predetermined period. There are several real-world examples where driver distraction was a condition, yet the driver-sitting-idly-in-the-driver's-seat threshold had not been met in years.

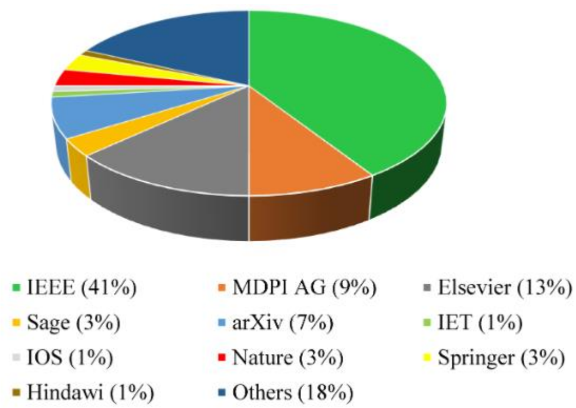

Fig :5: Percentage of manuscripts coverage between different publishers

5.1. Real-world Applications

Systems based on combining principles of control theory and machine learning can be used to derive effective control solutions for a range of vehicle-related applications. In recent years, interest has surged in end-to-end learning formulations, where raw inputs from a vehicle's sensors can directly be processed to derive control actions. However, in practice, these schemes require an inordinate amount of labeled training data to develop accurate models that can deal with the wide range of conditions found on roads.Integrating edge AI with model-based control provides better network design and architecture flexibility and can lead to novel model-based formulations that can leverage data sources in an auxiliary manner. Importantly, such hybrid architectures also provide good interpretability and allow constraints to be enforced using heuristic pre-processing algorithms.Control theory is at the core of a wide range of safety-based vehicle control systems. The use of formal logic-based control algorithms has been the cornerstone of high-assurance systems developed to date and are typically used to enhance AI-powered systems. Combining principles of the two methodologies in a principled manner has the potential to provide networks that can adapt to a diverse range of real-world and safety-critical scenarios.Control-based learning is the term we use to describe such integrations with machine learning paradigms, which allow network parameters to be updated by propagating gradients through the control algorithms. Schemes based on this methodology do not require a succinct end-to-end model and thus offer a higher degree of robustness. Moreover, while AI techniques are good at deriving discriminative models based on data evidence, constraints that encapsulate useful invariants and knowledge of the operating behavior in closed, known environments may not be naturally engendered from data.In contrast, control techniques can be used to encompass these constraints, which are necessary to ensure that the model behaves influenced in a way that guarantees safety and reliability.

5.2. Performance Evaluation Metrics

To evaluate the performance of the ML model, as well as evaluate the suitability of the approach for a given vehicle class, road condition, and scenario, it is necessary to define several evaluation metrics. Each metric emphasizes different aspects of model performance under diverse aspects of AV driving concerning various end goals and operational contexts. The critical performance evaluation metrics, their relevance, and some general guidelines are summarized in this article.Regarding objective performance, performance improvements through integration and calibration of the module are the fundamental aspects. It is beneficial to decompose the outputs of each module to evaluate and map their outputs to some relevant metrics. However, performance measurements concerning vehicle control systems such as path planning and vehicle dynamics need further attention. These performance evaluation metrics, as well as some general guidelines, are summarized in this study. In particular, it is beneficial to map the outputs of the trained models to performance measurements such as computational speed, frequency of operation, and specific vehicle control results. The design and relevance of the performance evaluation metrics are especially significant, as enhanced performance plays a key role in the broader capabilities and viability of the ML implementation.To effectively evaluate the performance of machine learning (ML) models in autonomous vehicle (AV) applications, and to determine their suitability for specific vehicle classes, road conditions, and scenarios, it is essential to define and employ various evaluation metrics. These metrics are crucial as they highlight different aspects of model performance across diverse operational contexts and end goals.Objective performance metrics focus on assessing improvements achieved through the integration and calibration of ML modules within AV systems. It is advantageous to decompose the outputs of each module and map them to relevant metrics. Specifically, for vehicle control systems such as path planning and vehicle dynamics, special attention is needed to ensure that the performance metrics accurately reflect the system's operational effectiveness.Key performance evaluation metrics include computational speed, operational frequency, and specific vehicle control outcomes. These metrics help quantify how well ML models translate into real-world operational efficiency and effectiveness. Guidelines for defining these metrics are critical as they directly impact the overall capabilities and feasibility of ML implementations in AVs.Furthermore, the design and relevance of these performance evaluation metrics are pivotal in ensuring that ML models enhance overall system performance and safety. By aligning the outputs of trained models with measurable performance criteria, stakeholders can effectively gauge the practical benefits and limitations of ML-driven AV technologies.In summary, a comprehensive evaluation framework that incorporates these performance metrics is essential for assessing the robustness, reliability, and applicability of ML models in AV environments. This approach not only supports ongoing advancements in AV technology but also fosters confidence in deploying ML solutions for safer and more efficient autonomous driving systems.

6. Future Directions and Emerging Trends

In this chapter, we presented an approach to developing next-generation vehicle control systems for passenger cars and vehicles used in driverless cargo transport. This approach relies on integrating AI and adaptive learning into control system design and using models that are trained on and operate within the hardware constraints of edge acceleration devices. We demonstrated the effectiveness of the AI-based adaptive approach with two examples of automated lane-keeping and adaptive cruise control systems for driverless transportation in highway conditions. Both tracks are driverless transportation underlying the same design principles that seamlessly integrate with existing best practices in transportation management. The development of these systems leveraged the increased capability of edge hardware devices and the rich ecosystem of software and tools designed for AI edge applications. Racing toward the edge in transportation is just one aspect of the relentless acceleration that the transport industry is experiencing at all levels, from infrastructure administration, and vehicle operation, to logistic management.Vehicle control systems can integrate the data and technologies of the edge that form the basis of an efficient, robust, and safe infrastructure. The tension between the flexibility to absorb uncertainties and measured actions conducted based on scenarios pulled from the library-controlled environment will still have to be balanced. The growing ecosystem of edge and edge AI tools to help manage this tension can be leveraged and integrated iteratively to both speed up the deployment of these advanced features and lower their development costs while improving safety. As edge technologies evolve, additional models—currently only instantiated on simulation or cloud-based systems—will be able to execute on the edge and interact with the rest of the transportation infrastructure in faster and more secure ways. Edge computing is supposed to form a clear symbiotic partnership with the cloud since certain other tasks—like computational best efforts such as training, autopilot feature development, and verification—are better carried out in a data center that offers the most computing power per watt (and per unit of CO2 emission).

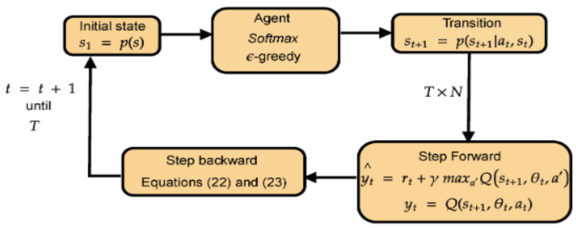

Fig :6: Simplified diagram describing the REINFORCE algorithm

7. Conclusion and Recommendations

Automotive technology is evolving rapidly, and the next evolutionary steps are expected to come in the form of vehicle autonomy, electric propulsion, and multilevel integration of smart circuits. Meanwhile, the concept of a digital twin, which is an edge computing construct, is increasingly being accepted and used in the automotive domain. The vehicle-integrated data analytics procedures involved in developing a digital car are pivotal to the method called predictive failure analysis, which is poised to create a profound impact on vehicle safety and reliability (VSR). After a brief introduction, the authors discuss how the use of advanced diagnostics can prevent failures and improve vehicle safety and reliability. Unmodified failure rates are inversely proportional to safety and reliability, and significant developments in data analytics and corresponding machine learning algorithms could result in AI-based predictive failure analysis procedures that can digital twins in the automotive industry: predicting changes to vehicle structure and physics, and various design, simulation, and management applications [21].

Simultaneously, the ontological structure of a vehicle can also be used to design architectures for a Vehicle Design and Operation Support System (VIDEOS). The technical details and system realizations in actual vehicles are used to enrich the mode-based ontologies. Consistency and reasoning are also confirmed.

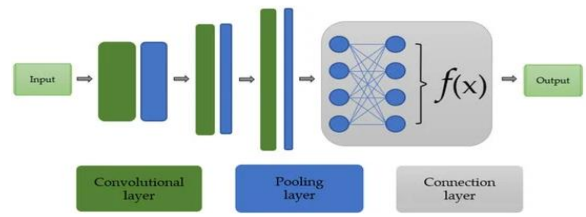

Fig :7: The basic structure of a CNN model.

8. Conclusion

The automotive industry, along with Information Technology, is converging with the emergence of Autonomous Connected and Electric Shared (ACES) vehicles. This not only promises the vision of safety but also peak performance. Towards achieving this goal, Edge Intelligence revolutionizes the paradigm of traditional vehicle control systems. With the ever-increasing advancements made in Deep Learning and Machine Learning models, Edge AI has demonstrated competencies in not only enhancing traditional vehicle systems but also paving the way for real-time implementation of such advanced models. In addition to this, the use cases that are employed act as essential ingredients for understanding societal impact factors and safety concerns. Having discussed the potential use cases, we offer beginning steps with research directions for future work.

With the advent of electric vehicles, the traditional rules governing the engine torque and operating regimes change. Edge intelligence models can be employed for data-driven optimization of strategies for the unique characteristics of electric vehicles. Health Monitoring is extremely critical for safety issues dealing with Autonomous Vehicles. In addition to these standard model and control problems, Edge Intelligence can also be instrumental in fueling the revolution of the two-wheeler space. With advanced capabilities of Edge devices to execute sophisticated control algorithms, the vehicles can be connected to the central authority of the Vehicle-To-Everything network in the long term, meeting both vehicular safety as well as performance promised by Autonomous systems.

8.1. Future Trends

The plethora of sensor data will lead to increasing use of AI at the edge. Edge computing will impact applications at the edge, and innovations in areas like edge GPUs, distributed AI, turning AI chips, edge privacy and data security issues, IoT devices, and ensuring low-power consumption with the need for AI to execute will all be critical enablers. Advanced perception, reasoning, decision-making, and control technologies will benefit from edge AI. The capital-effectiveness of integrated approaches that use AI for sensor fusion and decision support at the edge versus centralized processing will be an important factor impacting the way vehicles are equipped with computing resources.In the realm of autonomous vehicles, the top priority topics to be addressed for continued development are related to legal, ethical, and regulatory frameworks. There is an increasing need to build an understanding of the domain so reliable, safe, and sound systems can be developed, comply with ethical and legal assumptions and requirements, and show strong societal engagement focused on monitoring and discussing the main barriers. To harness the full potential of AVs, it is critical to address the challenges highlighted by the technology roadmap, which allows the setting up of an EU strategy that harmonizes national strategies, promotes the availability of common pilot zones, and ensures synchronization of the timeframe of implementation across all EU countries.

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