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The Convergence of AI, ML, and IoT in Automotive Systems: A Future Perspective on Edge Computing

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Abstract

Edge computing, where sensing, control, and intelligent processing occur near where data is acquired, is poised to be a fundamental enabler of several imminent disruptive future computing paradigms for emerging applications such as CPS, IoT, and more sophisticated AI-driven services. In this context, we posit the convergence of AI, ML, and IoT in automotive systems, the infrastructure required to enable it, and where edge computing will play a pivotal role in the real-world deployment of this ecosystem. We also review a few digital infrastructure technologies that can vastly enhance these next-generation digital automotive systems. This is examined through the investigation of real-world scenarios provided by our partner companies, the prominent Consumer Electronics Show (CES), and other sources. First, it is demonstrated through several industrial benchmarks that the proposed digital infrastructure technologies provide significant alleviation in terms of application accuracy, and at times even take the benefits beyond even 1x equivalent DNN accelerator-based systems in resource-constrained edge computing environments. After this, the challenges of designing and deploying them in real-world automotive systems are outlined. The paper concludes with the verifiable thesis that edge computing technologies need to play a significant role in the next-generation digital automotive system development so that ML-driven AI systems of the future are designed and deployed successfully in the field and can deliver their intent of providing superior user experience, enhanced safety, and convenience.

Keywords: Convergence of AI, ML, and IoT in Automotive Systems , 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

In recent years, widespread enhancements in edge computing have been realized through techniques of exploratory computing at the nano-scale, such as Artificial Intelligence (AI), Machine Learning (ML) in cognitive science, Intelligent Systems (IS), Intelligent Infrastructure (II), Internet of Intelligent Things (IoT) and Internet of Things (IoT), collectively driving the advancement of Cyber-Physical Systems (CPS). Edge computing achieves real-time response and decision-making. Autonomous systems utilizing embedded intelligence are realizing concepts such as Instant Intelligence (In-I), Automatic Autonomous Architecture (AAA), Real-Time Remote Reality (R3), and Driver Protection Space (DPS), collectively contributing to applications such as Industry 4.0, Connected and Autonomous Vehicle

(CAV), Advanced Driver Assistance Systems (ADAS), Intelligent Vehicular Systems (IVS) and Multi-Vehicular Systems (MVS). In communication for the new societal or economic value of 'cyber-physical-social-organizations'. AI proposes to distinguish intelligent behavior from structure, implementing algorithms capable of learning and consequently evolving.This paper reviews how AI and ML technologies, in association with the support of IoT, would drive embedded algorithms for smart devices in a seamless manner, realizing advanced applications to benefit automotive systems. Such embedded algorithms are becoming an integral part of most electronic control units used in automotive systems and would transform embedded systems at the edge into unique value-added devices with applications requiring ultra-low latency and high response times. Traffic condition monitoring, Intelligent Transportation Systems (ITS), vehicular communication cyber-physical capabilities. Finally, the importance of such key differentiators involves the examination of the unique characteristics as they relate to the capabilities for autonomous behavior management.Embedded algorithms play a pivotal role in enhancing automotive systems by enabling advanced functionalities such as real-time traffic condition monitoring and Intelligent Transportation Systems (ITS). These algorithms are crucial for enabling vehicular communication and cyber-physical capabilities, which are essential for improving road safety and traffic efficiency. As these embedded systems evolve, they are expected to deliver ultra-low latency and high response times, transforming into value-added devices capable of autonomous behavior management. These characteristics underscore the critical importance of leveraging advanced embedded algorithms in modern automotive electronics.

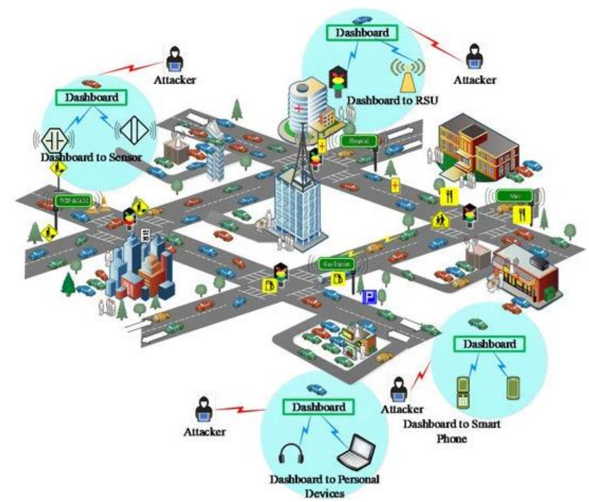

Fig :1: In-Vehicle security scenarios with possible threats.

1.1.Background and Significance

Intelligent transportation systems date back to the 1960s when the earliest work in this field was reported. Siemens' invention for detecting trains in 1835 consisted of a pair of copper strips placed between the rails. The passage of a train wheel over it would short-circuit the electrical connection between the strips and, in effect, trigger an alarm. This invention was the first primitive system to have used the principle of track circuits, which falls under the realm of automated train detection systems. This system later evolved to include an inductively coupled coil to transmit data and power, a convenient alternative to wire-based systems.In the mid-1900s, humans controlled these over-the-wire systems using telephones and switchboards to help trains navigate their way through complex, interconnected networks. This marked the inception of systems that aid humans in managing train movements using wired communication and line-status indicators. Throughout its history, this system went through numerous developmental stages, transitioning from wire-based communication to wireless communication. Although these systems were carried out for numerous decades, improvements leveraging technology were limited to line communication and command/control infrastructure.Safety, congestion management, and environmental concerns are the most visible aspects that motivate the modernization of transportation systems, having a direct link with the automotive industry. Data-driven decisions have been widely advocated to improve traffic safety, reduce delays during incidents, and mitigate the environmental impacts of the transportation system. Additionally, with advances in communication and wireless technology, there have also been significant advances in the field of sensor technology and high-speed computing, i.e., Big Data, which can help the auto industry better understand and respond to ever-evolving transportation needs.With the emergence of these technologies, there is the potential for connected vehicles to interact with the transportation infrastructure, enabling the development of cooperative schemes. Over the years, there has been widespread use of simulators, and indeed, machine learning and IoT are increasingly being used to support the modernization efforts to ensure safe, efficient, reliable, affordable, and equitable transportation systems.

1.2. Research Aim and Objectives

Aim: The broad aim of this research is to systematically identify factors of the convergence of AI, ML, and IoT-based automotive systems with other main vehicle automotive components for creating the future perspective of more autonomous driving, which includes vehicle-to-vehicle communication and traffic congestion information sharing. In this context, the present paper gives an initial insight into various AI, ML, and IoT-based vehicle technologies and also emphasizes edge computing. In-depth continuation of this work later, we review the Risk Perception Data Fusion at Edge to Fast Comprehend Autonomous Driving.Objective: The objectives of this study are as follows: - To systematically examine the AI, ML, and IoT-based automotive systems of intelligent driving vehicles. - To understand the technological issues and the benefits that can be achieved by AI, ML, and IoT through the convergence of edge computing. - To deduce a future direction of focus for autonomous driving, specifically vehicle communication, to overcome the adverse issues of autonomous driving. - To establish awareness of vehicle traffic congestion information gaps at the speed of the pulse of autonomous driving times. - To help policymakers and auto manufacturers obtain information that has long been missing from team members to make final decisions.

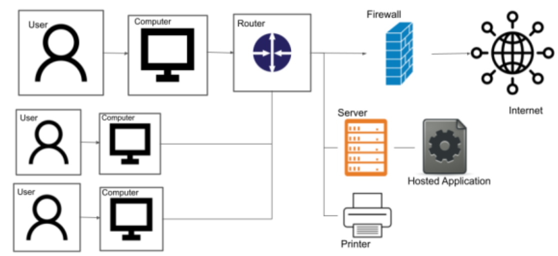

Fig:2 Simple Network Structure

2. Fundamentals of AI, ML, and IoT in Automotive Systems

This section will provide the basic definitions of AI, ML, and IoT from the point of view of the automotive domain, and briefly overview EDA challenges and solutions in automotive systems. Then, it will motivate why AI, ML, and IoT are crucial innovations for future automotive systems. Finally, from an application-oriented perspective, the goals of seamlessly integrated AI, ML, and IoT technologies in the automotive domain will be discussed. This section is for readers who are interested in the basic and essential knowledge about AI, ML, and IoT related to automotive systems, and those who are not very familiar with EDA challenges in the automotive domain. Therefore, the discussions here do not focus more on technical details, but instead, they give readers who are unfamiliar with some of the EDA challenges a guide to further reading sections that dig deeper into technical details with applications.AI, ML, and IoT are the most innovative technologies of Industry 4.0, and cars with these innovative technologies will revolutionize the automotive domain. These innovations are transforming cars from passive to active machines. An AI-powered car observes, learns, and makes its own decisions in coping with various interactions with its environment. It may react differently in different environments and with different conditions. With AI, a car does not have to be trained only for specific situations. Requirements for task training for an AI-powered car are not the same as that for an autonomous car. The latter trains for probable driving environments, behaviors, and scenarios, and has decision-making capability for safe driving in those scenarios. The former is more decision-making on when to take pre-defined action when detecting emergencies. Its decisions can be pre-designed, pre-implemented by ML, and implanted to task decomposition for taking immediate actions without any human intervention. AI technologies are evolving with better interaction, communication, and intelligence. With its self-learning ability, a car with AI technologies can be considered as a self-taught/learning system as its human driver. And at a specific assistance level or intelligence capability, it may not be different from a human driver. Automotive AI technology is also referred to as automotive AI cockpit, where all capabilities of the human driver are being replicated in a car in terms of observer and decider. With integrations of diverse capabilities, an AI cockpit has different cadres of AI. These different cadres of AI can co-work with each other autonomously, and communicate results and environmental changes within a local scope/area of their domain/zone. An AI cockpit can be viewed as a protocol-aware network of different automotive AI technologies, communicating results with each other to produce essential results for assisted driving.

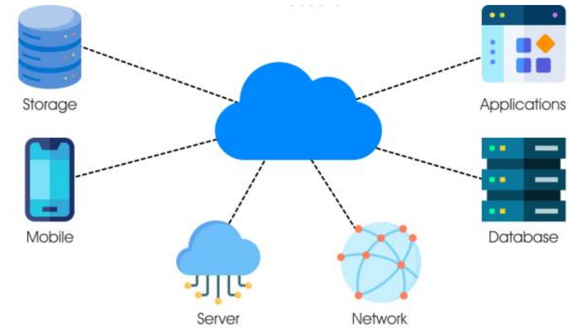

Fig :3 Cloud Computing

2.1. Overview of AI, ML, and IoT Technologies

In this section, we will provide a brief introduction to the technologies that are going to drive the 6th IT revolution, namely AI, ML, and IoT.Artificial Intelligence (AI) is generally defined as the capability of machines to imitate human cognitive functions. One of the simplest methods of implementing AI is rule-based encoding, which allows the machine to make decisions based on the stored rules. Better accuracy could provide performance enhancements. A popular form of ML is the training of models using large amounts of datasets. The Neural Network (NN) is an advanced ML method that mimics human brains with artificial neurons, which perform tasks such as learning, clustering, and function approximation. Both ML and NN offer a high level of accuracy, but these algorithms are complex and require time-consuming and high-speed computing capabilities, making them unsuitable for use in resource-constrained automotive edge devices.

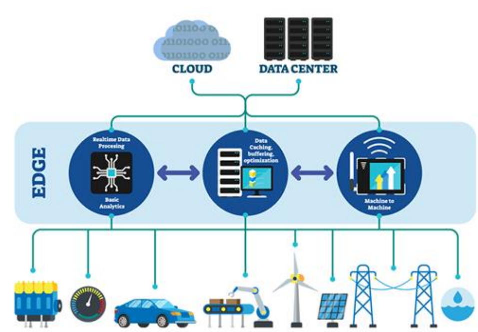

Fig 4: Edge Computing

2.2. Applications in Automotive Industry

Driven by the explosion of IoT, mobile devices, and wireless networks with high bandwidth, edge computing has the potential to transform the landscape of future automotive systems. The problems of traffic jams, parking, safe driving, navigation, and fuel efficiency are also the main relationships between the future smart city and future automobiles. In the existing literature, we summarize the prospects in one of the following three aspects: teleport; big data; and help to intelligent AI, as shown in Fig 5. However, in the age of self-driving and IoT-based car-city fusion, we must re-characterize the future of the automotive manufacturing industry, where AI, machine learning, and edge computing are helping to promote the two main trailing gears of car space to become the main factors of the engine: Car-to-Car/Car-to-Pedestrian (co-Teleport), Car-to-Cloud; autonomous driving, energy control, ADAS (Advanced Driver Assistance System).Currently, machine learning for the next generation of automotive use cases, including ADAS systems (automatic driving auxiliary systems), requires performance and real-time insights into the data. Edge computing delivers these features. Such a system is a technological innovation, such as Tesla, NVIDIA DRIVE, and BMWat, which leads to the medium-term boom of the L4 autonomous driving street-alone ratio. This technology can operate processes on edge devices or gateways, to perform content filtering at the front end, or create specific IoT solutions, which already have local and fast decision-making ability and backhaul data stream functionality. Edge artificial intelligence (AI) and data center AI will evolve in a complementary and independent manner in and outside the automobile in the next 2 to 3 years, including the Vetrov Center for the reflection of neural networks, quantum AI, future networks, spiking AI's new energy consumption model, etc., all the paths to the development of L5-level autonomous driving will be opened, or during that stage, the self-driving car technology will be born.

3. Edge Computing in Automotive Systems

Automotive systems need more computation to satisfy humans with the most intriguing applications. Eventually, it requires vast amounts of data and high computational powers, sometimes overriding available resources such as computation and memory, which are often the final limitations in the distributed system scenario. The next-generation systems are not only data and compute extensively, but also real-time and online requirements. Due to remote hard drive systems and computation latency, Localized Artificial Intelligence (AI) is used in real-time processing in classification and binary function of cause effects. This paper discussed a model of edge-localized AI systems in distributed architecture for real-time automotive telemetry data exploitation. The proposed model is advantageous for machine learning on edge push inference, Data cybersecurity, and AI online learning. It is easy to integrate your model and re-learn a new task with reported cases.Edge computing is a novel computing architecture for Internet of Things (IoT) systems. The purpose of edge computing is to migrate applications and services closer to end users or data sources, to reduce latency and bandwidth. Many of the novel applications like smart cities, healthcare, industrial automation, and Unmanned Aerial Vehicles (UAV) are highly dependent on latency, in addition to End-to-End resiliency, autonomy, privacy, and compliance. Furthermore, edge computing systems are required for on-device AI. AI is currently in its heyday, which could be used for human detection, object tracking, speech recognition, and gesture control on consumer electronic products. The latest market trends are demanding Light AI processing, which could benefit from edge computing technology, thus the most intuitive designs in edge computing will be beneficial in the future with convincing prospects. The distribution in edge computing enhances the robustness of the system.Edge computing represents a paradigm shift in how computational tasks are handled in IoT and automotive systems. By moving computing resources closer to where data is generated, edge computing reduces latency and bandwidth usage, crucial for applications requiring real-time responses like autonomous vehicles and smart cities. This approach not only enhances performance but also addresses challenges such as data security, privacy concerns, and compliance with regulations.In the realm of AI, edge computing facilitates on-device processing for tasks such as human detection, object tracking, and speech recognition. These capabilities are increasingly important in consumer electronics where responsiveness and efficiency are paramount. The trend towards lightweight AI processing aligns well with the capabilities of edge computing, making it a pivotal technology for future innovations.Moreover, edge computing systems enable continuous learning and adaptation through AI models deployed at the edge. This capability supports dynamic environments where real-time data analysis and decision-making are essential. As industries explore the potential of edge computing, advancements in distributed architecture promise to bolster system robustness and scalability, paving the way for transformative applications across various domains.

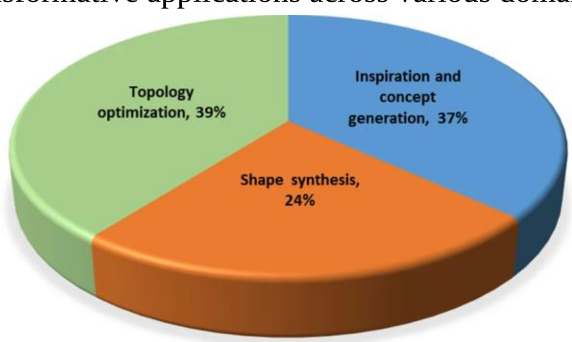

Fig :5 AI techniques and their prevalence in different design stages

3.1.Definition and Key Concepts

The concept of artificial sensor systems has appeared where a computing device needs to interface with the physical world and generate results based on the information it senses or gathers. Such systems need new types of machine perception and problem-solving capabilities. They require the ability to accept inputs corresponding to physical phenomena or knowledge and then generate results that synthesize action in the physical world. These capabilities have the requirement of converting physical phenomena or knowledge into digital data representation and then applying perforated logical operations to determine specific actions. We aim to create a fast, small, low-power physical equivalent of a human logic system. Such capabilities can be used to form the basis of a new generation capability in systems and assist in monitoring and controlling the physical environment. The underpinnings of the processing are provided by artificial sensors, and it is enhanced by predictive (dynamic) modeling that can predict buying behavior or human emotion based on certain data. These dynamic models can also predict the physical and functional state of an individual or a system.Artificial sensors can be classified as having two main forms of capabilities: possession of person – perception or knowledge-based retrieval senses, actions, etc., and possession of person – communication or affective senses. The artificial perception sensors embody a process with the following attributes:1) Sense-modify-act cycle: It should be quick, efficient, and use data acquisition using physical resources.2) Multimodality: Should be able to derive information from different entities such as different colors, textures, or orientations of an object.3) Attention: Focus on one subject of interest over another that is relevant to the task, context, and learning methodThe process of communication can be seen as sensing – extracting information from data, leading to perception – social understanding of social cues and context – eventual response in real life based on the diverse social knowledge or understanding. These functionalities support several intrinsic characteristics that need enhancing individual capabilities of artificial sensors to add current value just as the individual abilities of people combine to produce a whole that is more valuable in most social settings. The next generation of sensors is at varying stages of development for researchers and practitioners in many different areas. Infotainment entities such as smart photo and music browsers and large-scale video surveillance systems have already shown notable research and commercial potential. These latest iterations on long-standing research issues should help us to achieve longer-term goals.

3.2. Advantages and Challenges

In this era of the Internet of Things (IoT), the devices on which edge computing takes place have improved a lot compared with the devices of the previous era. Without edge computing, much horsepower and time are needed to push all raw data collected from large-scale sensors to the cloud-level computers to perform centralized data analysis, leading to a heavy burden on big server farms, often causing large battery power consumption in the case of wireless data transmissions, and ruining the low latency because of much longer data processing times.

Without edge computing, vehicle location-related computational tasks may suffer degradation in comparison to the perfect low-latency task execution in the cellular vehicle-to-everything (C-V2X) mode, where the cellular base station is only connected with the self-interested carrier aggregation module, with the inferable result pushed to an onboard processor to decide whether to trigger an immediate vehicle emergency stop on the signal light phase of one of its neighboring junctions.

Today, end devices are enhanced with more AI and computationally intensive tasks. Edge computing and data analysis, storage, and prediction have started to become the norm rather than the exception. Such a solution typically enhances task execution with fiat quality of service, shorter reaction times, and lower energy consumption, while leveraging abundant and valuable data around their deployment sites. Overall, with effective edge computing infrastructure, desired task executions can bypass long-distance communications toward centralized powerful cloud centers, achieving both lower latencies and lower bay power of wireless devices, while allowing other intended tasks of big server farms to remain undisturbed.

However, caution is needed because attention should be paid to the total workload involved with so many distributed edge computing devices and the spatiotemporal complexities of so much big data to prevent the resulting heavy multi-layered edge architecture from creating unintended energy consumption.

4. Integration of AI, ML, and IoT with Edge Computing in Automotive Systems

In almost all industry sectors, leveraging IoT with big data is the prime task to offer advanced solutions for consuming reliable and low latent information. To process this big data generated at the end device, different innovative solutions are proposed, and the concept of IoT integrated with Edge Computing (EC) is mainly introduced to offer advanced solutions like reducing latency, increasing system reliability, and conserving bandwidth over the cloud. To have a reliable and flexible design, the emerging three key technologies, Artificial Intelligence (AI), Machine Learning (ML), and EC are used in automotive systems to have attractive solutions. Integrating these with the IoT concept helps predict demand, optimize production and delivery, and increase end-to-end system and environmental reliability. Hence, this review mainly focuses on the integration of AI, ML, and IoT with EC in emerging automotive systems.Artificial Intelligence (AI) in the automotive domain is exponentially increasing due to its capabilities to offer autonomous vehicles, cooperative driving, advanced navigation systems, vehicle health management, driver safety assistance, connected traffic management systems, urban mobility, secure networking, emergency management, etc. Driverless vehicles are getting ranked in the current transportation system to decrease road accident rates by decreasing the number of driven vehicles by humans. This is mainly achieved by integrating several sensing technologies inside the vehicle like cameras and a neural network with a supercomputer to build a super AI system. Such AI technology needs to depend on several factors and converge towards concepts like IoT and Machine Learning. Deep Learning (DL) is mostly settled within ML to offer AI. AI cannot run without data, but hundreds of thousands of sensors like radars, cameras, GPS, LIDAR, V2X communication, motion sensors, ultrasonic sensors, long, short range, and stereo vision.

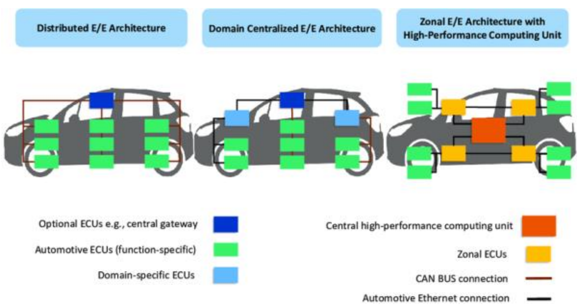

Fig :6 Distributed E/E Architecture

4.1. Benefits of Convergence

Using the converged AI, ML, and IoT (with Edge Computing support) approach, the system is capable of generating and comparing the data for providing services like ErV, RDP, C/AV, etc. from vehicles/businesses of people in a way that was not possible with the PLC/Embedded Conventional approach. With the converged AI, ML, and IoT models, it is possible to monitor, control, and provide customized, energy-efficient, economical, and non-economic services for cars, vehicles, buildings, etc. One simple example that is impossible with PLC/Embedded Conventional architecture is the monetizing capability of helping identify a previously unknown malfunction in an automobile. In the reported burning incident of the Tesla Smart electric car, two persons who understood the electronic control software system voluntarily helped the owner of the burning Tesla car, which was a very commendable act. By implementing the converged AI, Machine Coding, and IoT in the control achievement section of the Tesla Smart Car, it is also possible to monitor, regulate, control, and assist in the collapse/damage to vehicles like the military MedEvac helio-assisted explosion area. By knowing the nearness, location, and road obstruction at the time of accidents and alerting the relevant authorities, a speedy rescue operation can be incrementally improved. At this moment in time, a collapsed and burning car disaster causes a high number of human deaths on the road. For implementing the Control Algorithms of the Tesla Smart car, it is mainly necessary to integrate the image processing and simulating capability into the moving control algorithms. The integration facility is also possible with the converged AI, ML, and IoT Motor control system.

4.2. Use Cases and Examples

Use Cases and Examples. In this section, we present realistic use cases where the ever-larger amount of data generated by an intelligent connected vehicle, or collected from its environment, can be analyzed and processed close to where they are generated. We categorize the use cases based on commonly accepted functionalities that can describe the overall needs to guarantee that cars and other road participants can work together to make the present and future roadways safer and more efficient.Safety-Related Functions. Available solutions include accident risk prevention, vehicle control automation, autonomous driving support, and autonomous driving. These functions can be provided by techniques such as gas/liquid leak detection, hazard zone detection, traffic and road quality state monitoring (e.g., tires making contact or not contacting the road surface), advanced driver assistance, vehicle post-driving analysis, energy-efficient driving, road operator monitoring, and handling of lane change maneuvers. Third-party functional safety is a key enabler for these techniques to become a reality. It allows the challenging behavior of cooperative systems (e.g., cars and road infrastructure components) to be addressed and the operational design domain in which the system can operate to be defined, ensuring that the system cannot be the cause of dangerous situations. Third-party verifications like safety analysis, type of violation analysis, and safety validation are essential for any new proposed safety function when it is not properly addressed by predefined and regulated standards. By considering edge computing, it is possible to use the data resulting from different sensors installed on the vehicle (e.g., LIDAR, cameras, and accelerometers) in fast and efficient algorithms that act directly over deciding the desired vehicle route and speed, monitoring and ensuring the driver's state (managing signs of fatigue or inattention), and evaluating the vehicle condition before and after a desired driving route. Efficient communication protocols between vehicles and road infrastructure components ensure the necessary data is delivered to the places where different computing tasks run. Other techniques that need the availability of large clusters of connected or co-located data to be effective are driving automation, intelligent vehicle decision-making control, braking systems; and acceleration control (e.g., skidding, slipping and its effects, tire-road pressure, and traction control). For example, a vehicle applying emergency brakes affects the motion of the vehicles immediately situated behind, including the vehicles using the adjacent lanes if the driving is not autonomous. To avoid the occurrence of mass collisions, the vehicle in autonomous driving operation should use information exchanged among smart vehicles obtained from dedicated infrastructure along a country-wide expressway. To do so, we can use a publicly available national expressway guide for those in need of reserve service under extraordinary circumstances. The collided vehicles on the road must immediately stop and inform the detected fault, defect, or cause. The relevant information is deliverable by calling a prejudiced management.

5. Future Trends and Research Directions

This Outlook section provides an overview of future trends, innovations, and recent research developments that are contributing the most to the integration of AI/ML and IoT in automotive systems. We highlight a set of future trends that are being set in research themes at the (near) vehicle edge to support future functional requirements and architectural properties for advanced vehicle-induced AI/ML and IoT technologies.Given the exponentially growing demands for in-vehicle processing energy, short latency, and massive storage space of data owing to a massive growth of the interconnected and distributed AI/ML and IoT technologies and services, there are a set of understudied architectural-property-aware deployment and runtime support challenges that must be fulfilled at the vehicle edge to ensure that these innovative automotive technologies perform efficiently and effectively.Towards this goal of identifying and emphasizing current challenges along these lines, in the rest of this section, we provide our proprietary emerging automotive edge perspective on the functional technologies and research directions that will shape the deployment of subsequently related future (mostly ground) settings of AI/ML and IoT technologies and services to provide out-of-vehicle demanding (good) VISION reinforced services and experiences.

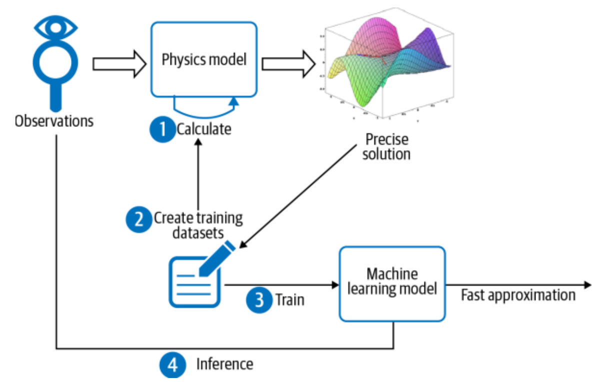

Fig :7 physical model capable of computing

5.1. Emerging Technologies and Innovations

In the automotive sphere, there is a clear trend toward harnessing the power of data and subsequent analysis to achieve a paradigm shift in different traditional business sectors. This raises a broad range of innovation opportunities. The anticipated emergence and convergence of various technologies, platforms, and ecosystems are enormous. A few of these are enabling cost-effective ADAS, creating new maintenance and logistics business models using predictive analytics, improving driver and passenger health and wellness by analyzing health and wellness data, creating automotive personal assistants, and creating new traffic management systems. The big data and intelligence foundations that are being built have true transformative potential.The connectivity of the car to the IoT is expected to rise substantially in the coming years. It will reach an outstanding number of over 250 million cars by 2020. Several of the main car manufacturers have even set the objective of defining the car as the main element of a network of concurrent intelligent services. They have become real service platforms, such as, for example, BMW's ConnectedDrive, GM's OnStar, Audi's Connect, and others. They all offer services consisting of vehicle remote monitoring (zoning, anti-theft functionalities, statistical information about the car, etc.), remote diagnostics, and different mechanical and electric system monitoring services. They also offer in-vehicle systems for navigation, connectivity, and telematics. In the future, the spreading of V2V and V2I systems should make it possible to add monitoring services of the context around the driver, thus enhancing and personalizing the support given to the user.

5.2. Challenges and Opportunities

There are several challenges to building a cost-efficient, scalable, and distributed computing architecture for enabling effective AI, ML, and IoT operations in edge or fog settings. In the design of such solutions, multiple factors, such as quality-of-service (QoS), energy, latency, performance, and fault tolerance need to be taken into account. But all these objectives are conflicting and multiple constraints cannot be satisfied simultaneously in large distributed settings. Furthermore, in IoT environments, nodes can join or leave the network at any time. This necessitates a dynamic reconfiguration of the network architecture to maintain high performance at a reduced cost. Indeed, in the rush to avoid the cloud, a designer of edge or fog computing systems may end up creating a server-rich dumb end.AI, ML, and IoT applications targeted towards the automotive domain need to shift their focus towards developing resource-aware computing solutions that are based on building on the following fundamental attributes of edge or fog settings: localization, aggregation, and role, and employ self-configuration, self-optimization, self-healing, and self-protection mechanisms. This paper showcases how these fundamental principles can be applied in automotive scenarios to perform both vehicle-based as well as sensor-based processing operations that can lead to useful applications that are developed with minimal dependence on the cloud. We show how AI, ML, and IoT can demonstrate their increased value proposition for automotive applications by working together on the edge rather than mostly working in individual silos as they do today.’

6. Conclusion

In this paper, the promising potential of the compact interplay of IoT, AI, and ML is contemplated as the up-to-date smart IoT edge computing of future convictions on automotive systems, and a great deal of surveys on the edge and fog computing frameworks expected to fulfill their prospects is plentifully investigated. HIML vision and AI-enabled countersignature recognition of ovum are only distant examples of the modern rapid augment of IoT-facilitated AI technology, in particular for a mutual energy application with accentuation on the landfill. As we see, the intelligent autonomous driving application is multifaceted, and we will only spotlight the demodulator of the smart accelerometer for accident detection.

In the subsequent part, future expectations from the standpoint of following the intelligent miniature edge concept of the HIML embedded manipulation of AI algorithms in the smart training stage derived with the application of the already mentioned IoT in combination with the Cloud are critically elaborated. In conclusion, we critically summarize the content of the questionnaire paper, challenge the opportunities of the further progress offered to realization of the NLQ smart IoT ITS future implementation of edge computing in automotive applications, and evidence with the wooden creative IoT and AI acceleration project.

6.1 Future Trends

Automotive systems design is undergoing many revolutionary changes. These trends and challenges are likely to gain further impetus and are likely to endure. The judicious combination of various enabling technologies providing sophisticated functions makes the design of next-generation vehicles a truly multidisciplinary field. It will require the synergistic combination of sensor and actuator technologies working in close conjunction with electronics, communication, and signal processing. While there has been significant work in AI, machine learning, and IoT for automotive systems, most literature treats the three aspects as separate modules. This paper identifies the problems in several milestones that should be solved to fully realize the convergence of AI, ML, and the IoT and how edge computing is required to solve those problems efficiently. The realization of the proposed work can lead to automotive systems that learn, evolve, and make intelligent decisions in an adaptive and real-time manner during all phases of vehicle operations and even parking times.

In this current discussion, the hardware platform for the realization of the future automotive systems is centered around embedded systems with the integration of AI and IoT. This includes intelligent edge nodes, information infrastructure with the cloud, embedded sensors and actuators, and embedded automotive systems. One possible hardware platform to realize the proposed future AI, machine learning, and IoT for automotive systems is to adopt NVidia Tegra SoC, which requires the integration of embedded sensors and actuators. It is known that communication over a wireless local area network (WLAN) consumes less energy compared with 4G and 5G. However, when vehicles are away from network coverage, 4G and 5G should be considered. Therefore, embedded systems as edge nodes are the first step to developing this research in future work. With the rapid developments of electronics, it can be expected that most MSA will be hardware accelerated with a low power consumption of about 10-20 W shortly. The use of MSA can lead to hefty energy savings, and the MSA has the potential to be integrated within the computers onboard smartphones and other communications equipment. Edge computing effectively manages the automotive systems of the future, which are real-time, energy-efficient, and feasible for use

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