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Artificial Intelligence for Electronic-based Systems in Safety Applications

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1. Introduction

In today's world, electronic systems have become indispensable in technologies spanning the Automotive and Robotics sectors. Electronic-based safety systems (EBSS) play a crucial role in autonomous solutions, ensuring stability and precision in their operation. For instance, in autonomous vehicles, EBSS enable the integration of sensor data and AI algorithms, supporting collision avoidance systems and real-time decision-making optimization. Similarly, in robotics, EBSS are responsible for the reliable functioning of key features, such as navigation in dynamic environments and execution of precise tasks, ensuring user safety. Innovations based on artificial intelligence, deep learning, robotics, and computer vision have the potential to revolutionize the design and validation of these systems. A critical challenge lies in ensuring their reliability and predicting their long-term performance.

This article aims to present state-of-the-art solutions in the application of artificial intelligence to electronic-based safety systems, with a particular focus on robotics, computer vision, and large language models (LLMs) in the context of environmental perception and autonomous systems. The technologies discussed aim to reduce development cycles and enhance system reliability, translating to resource optimization and the implementation of cutting-edge solutions in the Automotive and Robotics sectors.

2. Application of Artificial Intelligence and Deep Learning in Electronic-based Systems

a. Sensor data analysis for a real-time diagnostics

The integration of Artificial Intelligence (AI) and Deep Learning (DL) into Electronic-Based Systems (EBS) significantly enhances real-time diagnostics, particularly in safety-critical applications such as robotics and autonomous vehicles. Sensors play a crucial role in EBS by providing real-time data essential for monitoring system performance and detecting anomalies. These sensors measure various parameters, such as temperature, pressure, and vibration, generating voluminous and complex data that require advanced analytical techniques for meaningful insights.

AI and DL methodologies are particularly effective in analyzing sensor data. One of the primary applications is anomaly detection, where machine learning algorithms identify patterns within the data to establish a baseline of normal operating conditions. Deviations from this baseline can indicate potential failures or safety hazards. For instance, predictive maintenance models utilize historical sensor data to forecast equipment malfunctions before they occur, thereby preventing accidents.

In the context of robotics and autonomous vehicles, the ability to analyze sensor data in real-time is critical. Autonomous systems rely on a multitude of sensors, including LiDAR, cameras, and ultrasonic sensors, to perceive their environment accurately [1]. AI algorithms process this sensor data to make instantaneous decisions regarding navigation, obstacle avoidance, and safety measures. This capability is vital for ensuring safe operation in dynamic environments where quick responses are necessary.

Predictive analytics is another critical area where AI enhances diagnostics. By leveraging historical sensor data alongside real-time inputs, AI systems can predict future system states, which is vital for maintaining operational safety in environments where equipment failure could lead to catastrophic outcomes. Techniques such as regression analysis and time-series forecasting are commonly employed to achieve this.

Moreover, data fusion techniques allow AI systems to combine data from multiple sensors, enhancing the reliability of diagnostics. Deep learning architectures can learn complex relationships across different data sources, providing a comprehensive view of system health and improving decision-making processes. In autonomous vehicles, for example, fusing data from various sensors helps create a more accurate representation of the vehicle's surroundings.

However, several challenges remain in the application of AI for sensor data analysis. High-quality labeled datasets are essential for training effective AI models; yet obtaining sufficient labeled data can be difficult due to operational constraints or the rarity of failure events. Additionally, many AI models operate as "black boxes," making it challenging to understand their decision-making processes, which is particularly problematic in safety applications where transparency is critical. Furthermore, the need for real-time analysis imposes stringent requirements on computational resources and algorithm efficiency.

Looking ahead, the future of sensor data analysis in EBS will likely involve advancements in hybrid models that combine traditional engineering approaches with modern AI techniques. Integrating probabilistic machine learning with physical models can enhance reliability while adhering to safety constraints inherent in high-risk environments. Ongoing research into explainable AI (XAI) aims to improve model transparency, fostering trust among users in safety-critical applications [2].

In summary, the application of AI and deep learning for sensor data analysis represents a transformative approach to real-time diagnostics in electronic-based systems. By addressing current challenges and leveraging emerging technologies, these systems can significantly enhance safety outcomes across various industries, including robotics and autonomous vehicles.

b. Predictive maintenance of robots, vehicles and other EBSs

Predictive maintenance (PdM) is a crucial strategy for enhancing the reliability and efficiency of robots, autonomous vehicles, and other EBSs. By utilizing advanced data analytics and machine learning techniques, PdM anticipates equipment failures before they occur, minimizing downtime and maintenance costs. This approach is particularly significant in high-stakes environments such as manufacturing, transportation, and critical infrastructure.

The essence of predictive maintenance lies in the continuous monitoring of objects/equipment through embedded sensors that collect real-time data on operational parameters. This data includes metrics such as temperature, vibration, and operational cycles. By analyzing this information, predictive models can identify patterns indicative of potential failures. For instance, a study on autonomous vehicles highlighted how integrating Internet of Things (IoT) technology with machine learning algorithms can enhance the predictive capabilities of vehicle systems, allowing for timely interventions before failures occur [3].

In the context of robotics, predictive maintenance has shown substantial benefits. Autonomous mobile robots equipped with advanced sensors can perform inspections in hazardous or hard-to-reach areas, collecting high-quality data that informs maintenance decisions. These robots not only gather data but also process it using AI algorithms to generate actionable insights. Research indicates that such systems can significantly reduce mean time to repair (MTTR) by predicting equipment malfunctions before they lead to unplanned downtime.

Automotive manufacturers are increasingly adopting predictive maintenance solutions as well. With the rise of connected vehicles—expected to comprise 95% of new cars sold by the end of the decade—automakers are leveraging AI and virtual sensors to monitor vehicle health continuously. This capability allows for proactive maintenance alerts based on real-time usage data, improving vehicle reliability and safety while reducing costs associated with repairs and insurance.

Despite its advantages, implementing predictive maintenance poses challenges. Data quality is critical; noisy or incomplete datasets can lead to inaccurate predictions. Moreover, many predictive models function as "black boxes," making it difficult for users to interpret their outputs. Future research is focused on developing more robust algorithms that can handle imperfect data and improve model transparency. In [4], a comprehensive literature review on predictive maintenance is presented, covering the methods, standards, and application examples commonly used in this field.

In conclusion, predictive maintenance represents a transformative approach for ensuring the operational integrity of robots, autonomous vehicles, and other electronic-based systems. By addressing current challenges and leveraging emerging technologies such as AI and IoT, organizations can significantly enhance their maintenance strategies, leading to improved safety outcomes and operational efficiency.

c. Automated log analysis using Large Language Models

Large Language Models have emerged as powerful tools for analyzing system logs, providing significant advantages in extracting insights and automating responses in various electronic-based systems. System logs, which record events and transactions within software and hardware environments, are crucial for monitoring performance, diagnosing issues, and ensuring security. However, the sheer volume and complexity of log data can make traditional analysis methods inefficient and time-consuming.

LLMs excel in processing natural language and structured data, enabling them to interpret log entries effectively. By leveraging their capabilities, organizations can automate the parsing of logs to identify patterns, anomalies, and trends. For instance, LLMs can be trained to recognize specific error messages or unusual activity that may indicate system failures or security breaches. This capability not only accelerates the troubleshooting process but also enhances the accuracy of incident detection.

One notable application of LLMs in log analysis is their ability to generate human-readable summaries of complex log data. This feature allows IT teams to quickly grasp the state of a system without sifting through extensive log files. Additionally, LLMs can assist in predictive maintenance by analyzing historical log data to forecast potential future issues based on past patterns. For example, the study [5] presents an approach to applying LLMs for log analysis, demonstrating significant potential for practical applications.

Despite their advantages, employing LLMs for log analysis presents challenges. The models require substantial amounts of high-quality labeled training data to achieve accuracy in specific domains. Furthermore, concerns regarding interpretability arise, as LLMs may produce outputs that are difficult for users to understand or validate.

In conclusion, the application of Large Language Models for system log analysis represents a transformative approach for enhancing operational efficiency and security within electronic-based systems. By automating log interpretation and providing actionable insights, LLMs can significantly improve incident response times and overall system reliability.

3. Robotics and Computer Vision in Safety Applications

Perception is a key element in robotics, especially in systems where safety is critical. It allows robots to understand their surroundings and make decisions based on the data they collect. This section focuses on perception methods used in robotics, with examples from areas like autonomous vehicles, industrial robots, and human-robot cooperation. It also looks at the challenges of making perception systems reliable, accurate, and fast enough for real-world use. Perception in robotics relies on sensors such as cameras, LiDARs, and radars, which provide diverse data about the environment. Using this data, various algorithms can be applied to interpret the surroundings, including object detection and semantic segmentation. To achieve a coherent understanding of the world, data from multiple sensors is often fused. This data fusion enhances the reliability and effectiveness of individual algorithms, ensuring more robust and accurate perception in complex environments. An example of perception in robotics is the extensive use of various sensors in precision agriculture [6], where they enable tasks to be performed efficiently and, most importantly, in a safe manner.

a. Object detection

Object detection is a fundamental task in robotic perception, aimed at identifying and localizing objects within an environment. This process typically involves analyzing data from sensors such as cameras and LiDARs to detect objects and estimate their positions. Traditional vision-based methods are associated with overcoming challenges such as varying lighting conditions, occlusions, and environmental complexity. Modern approaches to object detection often rely on deep learning, particularly convolutional neural networks (CNNs), which enable high accuracy and real-time performance. Popular techniques include single-stage detectors like YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), as well as two-stage detectors such as Faster R-CNN, which combine region proposal networks with classification modules. In [7], available neural network architectures are presented in the context of perception and object detection.

Object detection is particularly important in safety-critical applications. Recent research focuses on improving detection accuracy in challenging conditions. The YOLO-TC model has been optimized for safety monitoring in tower crane operations, addressing issues related to complex lighting and cluttered backgrounds [8].

Contemporary research also focuses on enhancing detection accuracy in complex and dynamic environments. Article [9] proposes an innovative model fusion approach by integrating object detection with large language models. The models are fused using a single layer, which provides YOLOv8-n's object detection probabilities to the LLaMA2 (Large Language Model Meta AI). The authors achieved an improvement in autonomous vehicle responses, specifically in detecting small objects crossing the road and identifying narrowed or merged lanes.

Accurate and reliable environmental perception is one of the most critical aspects of autonomous driving and robotics research. Article [10] presents an advanced approach to object detection and tracking, combining the deep learning-based YOLOv8 object detection algorithm with LiDAR data fusion, resulting in improved accuracy and reliability in autonomous applications. The authors leveraged the strengths of both technologies where LiDAR provides precise distance measurements and 3D spatial information, regardless of lighting conditions whereas YOLOv8 enables fast object detection and classification in RGB images in real time. However, this fusion introduces several research challenges including (i) filtering ground points from LiDAR point clouds; (ii) calibrating data from different sensors; (ii) managing computational complexity when processing large datasets.

b. Segmentation

Image segmentation is a crucial task in robotic perception. It aims at dividing an image into meaningful regions to better understand the environment. This process allows robots to identify and classify different parts of a scene, such as distinguishing objects, surfaces, or background. Semantic segmentation, for example, assigns a specific label to each pixel in the image, enabling detailed analysis and decision-making. This is particularly useful in tasks like navigation, obstacle avoidance, and object manipulation, where precise scene understanding is essential. Segmentation is often performed using deep learning techniques, including fully convolutional networks (FCNs) and architectures like U-Net or DeepLab, which excel in pixel-level predictions. In [11], an overview of available methods is provided, highlighting current achievements and the challenges yet to be addressed.

Recent studies focus on sensor data fusion to improve segmentation results. In article [12], the authors explored a method for fusing 2D images and 3D point clouds, leading to more precise semantic segmentation in complex scenes. The solution involves combining 2D and 3D features, which are then further integrated using a shared multi-layer perceptron (MLP) and optimized through an attention mechanism. To enhance the model’s learning capability and segmentation accuracy in complex scenes, a knowledge distillation strategy was applied.

In study [13], the authors reviewed radar-camera data fusion methods for semantic segmentation, emphasizing the benefits of integrating these two data sources in autonomous applications. Based on radar-camera fusion datasets and methods, the paper discusses key challenges and potential research directions related to multimodal data and multimodal fusion. In the field of image segmentation, recent trends include the integration of transformer-based models, which capture long-range dependencies in images, improving segmentation accuracy in complex scenes. Models such as Vision Transformers (ViTs) and Swin Transformers outperform traditional convolutional neural networks (CNNs) by better understanding global context. Article [14] provides a comprehensive overview of transformer-based visual segmentation, summarizing the latest advancements in this field.

Advancements in real-time semantic segmentation are crucial for applications such as autonomous driving and robotics. Techniques like model pruning, quantization, and the development of lightweight architectures enable efficient segmentation models to run on edge devices without compromising accuracy. In article [15], the authors introduced an improved version of Fast-SCNN, integrating an attention mechanism and optimized feature extraction modules, achieving a better balance between accuracy and efficiency in urban scene segmentation.

c. Data fusion

The rapid advancements in sensor technology and increased computational power have significantly improved real-time data collection, enabling precise monitoring of various phenomena and industrial processes. However, the large volume and complexity of heterogeneous data pose significant challenges in data processing. Traditional data analysis methods, such as aggregation, filtering, and statistical analysis, are increasingly being supplemented by data fusion techniques, which provide a more comprehensive approach to data interpretation.

Data fusion in the context of environmental perception involves combining information from multiple sensors to create a more comprehensive and accurate understanding of the surroundings. By integrating data from sources such as cameras, LiDARs, and radars, fusion techniques can compensate for the limitations of individual sensors, such as poor lighting conditions for cameras or limited resolution in LiDARs. This process enhances the reliability and robustness of perception tasks, including object detection, semantic segmentation, and scene reconstruction. Common approaches to data fusion include early fusion, where raw sensor data is combined, and late fusion, which integrates high-level features or predictions. In [16], an example of data fusion is presented, showcasing the integration of object detection and segmentation results using data from a camera and a LiDAR. Data fusion techniques have evolved to enhance the resilience of perception systems in safety-critical applications. A comparative study of the latest automatic data fusion methods highlights the importance of integrating information from multiple sensors to improve classification performance in terms of accuracy and result stability [17]. In the context of autonomous driving, combining data from various sensors, such as cameras, LiDARs, and radars, helps compensate for the limitations of individual sensors. This integration enhances the reliability and robustness of perception systems, supporting tasks such as object detection and semantic segmentation.

Data fusion plays a crucial role in creating an accurate and reliable environmental representation in safety-critical systems. Recent research focuses on advanced fusion methods using deep learning. In [18], the authors present an in-depth analysis of deep learning-based data fusion methods across various domains, emphasizing their evolution and applications in recent years. Autonomous vehicles represent an innovative technology with the potential to make transportation safer, more efficient, and more convenient. Although existing solutions demonstrate some success, effective methods for addressing challenges such as road debris accumulation, which can obscure lane markings and traffic signs, are still lacking. Additionally, extreme weather conditions, including heavy rain, snowstorms, fog, and dust storms, can significantly impair sensor functionality, limiting their ability to detect obstacles, pedestrians, and other vehicles, thereby posing potential safety risks. In response to these challenges, [19] proposed a multi-sensor data fusion and segmentation method for multi-object tracking in autonomous vehicles using the Deep Q-Network (DQN). The proposed model integrates data streams from cameras and LiDARs and develops an intelligent object detection system by processing sensor images. The multi-sensor data fusion and segmentation approach for tracking multiple objects in autonomous vehicles enhances system performance and reliability.

4. Autonomous Safety Systems

The roles of Autonomous Vehicles (AV) in our lives cannot be ignored. Self-driving cars, Unmanned Aerial Vehicles (UAVs), and Autonomous Robots are the areas where autonomous vehicles are mostly used. Thus, autonomous safety systems are a developing topic that needs to be discussed and researched in the fields of cybersecurity and physical security. These systems are developed to predict security vulnerabilities, detect threats or intervene.

a. Autonomous Safety Systems for Self-Driving Cars

Vehicles that have various driving features that minimize human intervention or do not require any and that drive automatically are called autonomous vehicles (Self-Driving Cars). A classification system was published by the Society of Automotive Engineers (SAE) in 2014 to define and standardize the automation levels of autonomous vehicles. These levels consist of 6 classes, from level 0 (minimal automation, driver assistance) to level 5 (fully autonomous vehicles) [20]. Vehicles between levels 0 and 2 include driver assistance features. For example, level 0 has automatic emergency braking and blind spot warning, level 1 has lane-centering or adaptive cruise control, and level 2 has lane-centering and adaptive cruise control. Even if these driver assistance features are activated, you must drive the vehicle. Autonomous vehicles between levels 3 (conditional driving automation), level 4 (high driving automation,) and level 5 (full driving automation) include automatic driving features. Level 3 and 4 autonomous vehicles can drive under limited conditions. For example, level 3 has a traffic jam feature that takes over driving on highways and similar roads at speeds up to 60 km/h. When the feature is requested, you must drive. Level 4 has a local driverless taxi feature. It should be noted that these features will not work if the necessary conditions are not met. Level 5 features are the same as level 4, but at this level of autonomy, vehicles can drive everywhere in all conditions.

According to the Statista report, 60% of new cars sold globally are expected to have level 2 autonomy by 2025 [21]. Level 3 hit the road in Japan in 2021 with a small distribution by Honda. This was followed by Mercedes with certification in Germany and US in 2022 and 2023, respectively [22]. Meanwhile, Mercedes-Benz has received approval for level 4 autonomous driving testing on designated urban roads and highways in Beijing [23].
Waymo, the world's most experienced driver whose mission is to be the world's most reliable driver, is also among the autonomous vehicles. Waymo One, the world's first fully autonomous ride-hailing service, began providing 24/7 service without a human driver in many major cities in the United States in 2018. Thus, with its Waymo One service, Waymo can be considered one of the leaders in Level 4 autonomous vehicle technology. Navya, a French company, is also used today as a shuttle service in controlled areas such as private indoor areas, usually in level 4 autonomous vehicles. Tesla's Autopilot system in autonomous vehicles is classified as an SAE level 2 system. Tesla is constantly working on software and hardware updates to

reach level 4 autonomous driving capabilities (Full Self-Driving). Unlike other autonomous vehicles, Tesla uses cameras and artificial intelligence-supported software systems instead of lidar and radar. This approach aims to reduce costs and create a human-like perception system. The role and functionality of autonomous vehicles in traffic are rapidly expanding. Thus, safety systems in autonomous vehicles have become a crucial area that needs to be developed and expanded in today's world.

Safety systems in autonomous vehicles have been developed to ensure the safety of passengers and people around the vehicle and to ensure a safe journey. Sensors such as radar, lidar, cameras, ultrasonic, and infrared are used in autonomous vehicles to detect dangers and increase awareness. For example, radar helps vehicles determine their distance and is used in collision avoidance systems. Ultrasonic sensors help when parking the vehicle by detecting obstacles at low speeds. Software and artificial intelligence-supported systems such as computer vision and machine learning algorithms analyze data from sensors and enable faster decision-making. The sensors, software algorithms, and artificial intelligence we mentioned above support the safety systems of autonomous vehicles. So, what are these Autonomous Safety Systems?

b. Collision Warning System

Certainly, as the levels of autonomy in vehicles increase, the capabilities of their safety systems also advance. Sensor-based warning systems, which can be seen even in Level 0-1 autonomous vehicles, are the beginning of autonomous security systems. Fig. 1 gives examples of collision warning systems. Forward collision warning, lane departure warning, rear cross-traffic warning, and blind spot warning systems are systems that warn drivers against collisions. The forward collision warning system detects a possible collision with the vehicle ahead and warns the driver but does not intervene. The lane departure warning system warns the driver when the vehicle approaches or crosses the lanes. The rear cross-traffic warning system warns the driver of a possible collision in the area outside the rear-view camera's field of view. The blind spot warning systems alert the driver to the presence of a vehicle in the blind spot.

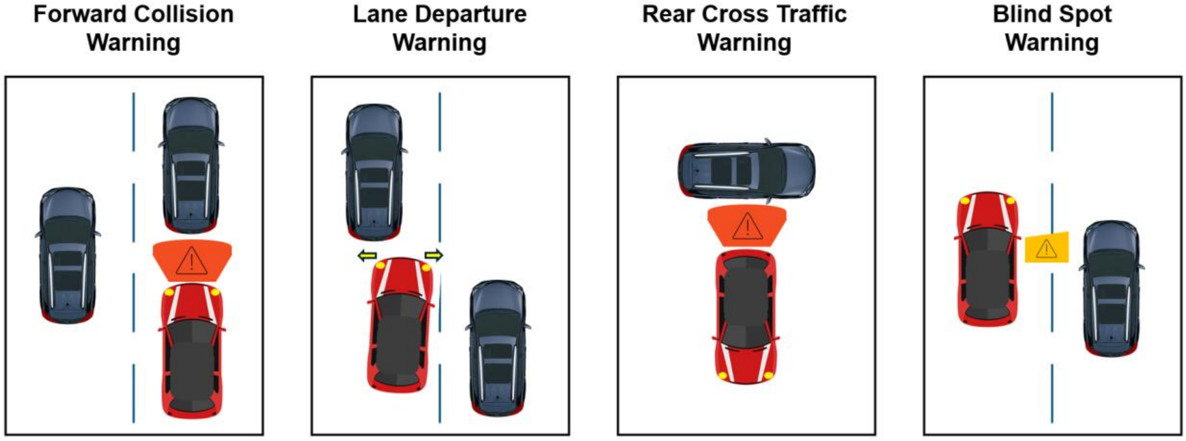

Fig. 1. Collision Warning Systems

In addition to warning systems, some autonomous vehicles have features such as adaptive cruise control, lane centering assistance, and lane keeping assistance that automatically keep vehicles at a certain distance from other vehicles, keep the vehicle in the lane when it goes out of the lane and provide control by helping to prevent collisions and ensuring a safe journey.

c. Autonomous Emergency Braking Safety Systems

The emergency braking system forms the basis of safety systems in autonomous vehicles. These systems increase vehicle safety by reducing driver reaction time and help prevent collisions, providing a safer ride for passengers, pedestrians, and cyclists.

As technology advances, safety systems in autonomous vehicles are transitioning from warning mechanisms to active intervention systems. The Autonomous Emergency Braking (AEB) system is one of the most common and effective intervention systems. The images in Fig. 2 are examples of automatic emergency braking systems applied in different collision scenarios. The images from left to right are: the automatic braking system in the event of a forward collision, the automatic braking system if the pedestrian in front of the vehicle is detected and the collision is imminent, the automatic braking system in the event of a possible collision while the vehicle is in reverse gear, and the automatic braking system when an attempt is made to change lanes if there is a vehicle in a blind spot.

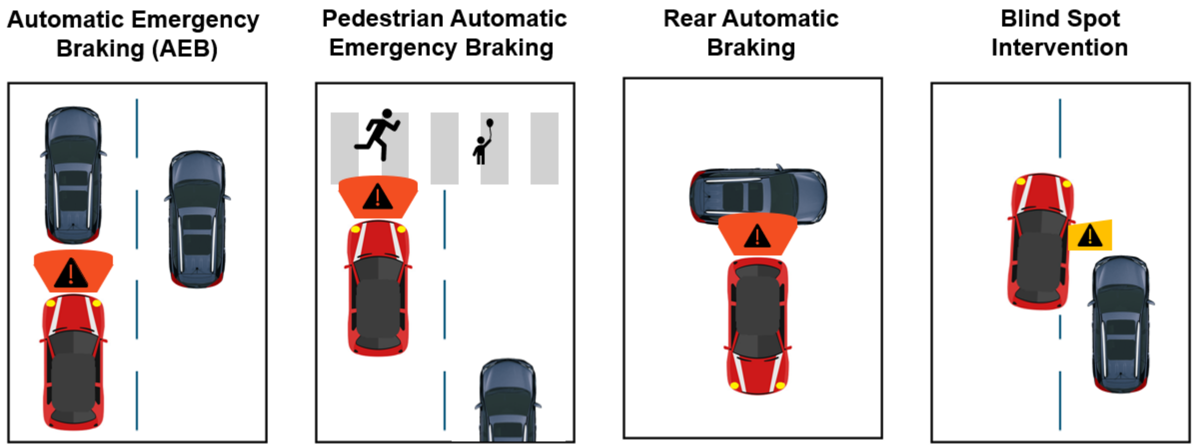

Fig. 2. Collision Intervention Systems

In a study conducted in the USA, the effect of AEB with pedestrian detection was investigated, and a 30% reduction in pedestrian injury crash risk was observed due to this autonomous safety system [24]. The study also noted that there was no evidence that the system was effective at speeds of 50 mph or higher, in dark conditions, or while the vehicle was turning. This research actually shows that AEB studies will continue to improve according to various conditions.

d. Predicting and Understanding Road Users' Behaviors

Behavior Prediction is a system that enables autonomous vehicles to predict and understand the future movements (behaviors) of other vehicles, pedestrians, and cyclists on the road with the main aim to prevent collisions. This system allows autonomous vehicles to avoid potential collisions and provide a safer journey. This system consists of several stages. First, data such as the speed and location of surrounding objects are collected from the sensors (Radar, Lidar, ultrasonic sensors) and autonomous vehicles' cameras. Then, this data is analyzed with mathematical models or machine learning, artificial intelligence models, such as whether a pedestrian is standing on the sidewalk or preparing to cross the road. After the system predicts and understands the behavior of the road user, it creates the safest action plan. The autonomous vehicle can then slow down, come to a complete stop, change lanes, etc. However, indeed, human or cyclist behavior is not always predictable. For this reason, these systems continue to be developed.

Waymo's Safety Research and Best Practices team conducted a study on how to measure surprising road user behavior. This study examines approaches to measuring surprising road user behavior using a machine learning generative model based on behavior predictions [25]. Another study [26] proposes a road user behavior prediction system by combining the Large Language Model (LLM) and Knowledge Graphs (KG) with Retrieval Augmented Generation (RAG) techniques. The study was conducted using two approaches: estimation of pedestrian crossing actions and estimation of lane change maneuvers. This study also demonstrates the expressive capacity of LLM in the prediction of road user behavior.

e. Autonomous Safety Systems for Autonomous Mobile Robots (AMR)

Nowadays, there is another type of autonomous vehicle that is widely used in the industry, logistics, agriculture, health sectors, and restaurants called Autonomous Mobile Robots (AMR), which can perform their tasks by perceiving their environment, analyzing it, and acting accordingly. AMRs are capable of operating independently without the need for external human intervention, relying on sensors, cameras, artificial intelligence, and software. They collect data with lidar, radar, ultrasonic sensors, and cameras. They perceive their surroundings, obstacles, and objects with artificial intelligence, Simultaneous Localization and Mapping (SLAM) technology, and choose the most appropriate path. Thus, they can quickly adapt to changes in the environment, draw a new route, and ensure a safe journey.

Lidar sensors have a major role in the safe movement of AMRs. Lidar sensors play critical roles in environmental perception, mapping, and detecting obstacles and avoidance in AMRs. For instance, the study [27] aims to increase operational efficiency and safety in industrial environments by leveraging Lidar-based collision avoidance to enhance Automatic Mobile Robot Transporters (AMR-T) with obstacle detection and avoidance capabilities. In another study [28], a dynamic navigation system using the Lidar sensor and stereo camera technologies was developed to increase the safety and efficiency of AMRs in industrial and urban areas.

Lidar sensors also play an important role in increasing the reliability of SLAM technology, which allows an AMR to create a map in an environment it has not previously known and to determine its position on this map. The SLAM algorithm and localization maps play a critical role in ensuring safety in AMRs. By enabling real-time mapping and continuous updates of the environment, SLAM allows the robot to navigate through unknown spaces while precisely determining its position. This capability facilitates efficient path planning and reduces the risk of collisions.

There are still challenges in designing control strategies to deal with collision avoidance and the absence of deadlocks in many applications of multi-robot systems. To address these issues, the online nonlinear Model Predictive Control (MPC) method was proposed to enable collision avoidance and deadlock-free navigation of multiple autonomous nonholonomic Wheeled Mobile Robots (WMRs) [29]. The simulations and experiments related to the study can be watched online at [30] and [31], respectively. In addition, for the safe and efficient operation of AMR, it is important to develop collision avoidance algorithms. For example, a predictive collision avoidance algorithm that tracks multiple objects simultaneously and predicts their speed and future positions has been proposed, which enables AMRs to navigate safely and effectively [32]. It has increased the performance of the collision avoidance system and contributed to safe and efficient autonomous systems.

f. Autonomous Safety Systems for Unmanned Aerial Vehicles (UAV)

Another well-known autonomous vehicle widely used in many fields such as agriculture, entertainment, logistics, and military is Unmanned Aerial Vehicles (UAVs). Safety in UAVs is a critical issue to ensure a safe flight. Lidar, ultrasonic sensors, cameras, and radars are used in UAVs to detect obstacles by making precise distance measurements and transmitting sensors and visual data used to detect obstacles and objects at close range. Moreover, UAVs have algorithms used to prevent collisions in emergency situations called fail-safe operations. A safe landing system is one of them and allows the UAV to land by determining a safe landing point in case of emergency. Secondly, emergency stops ensure that the UAV's engines are stopped in case of emergency (crash, battery problem, etc.). Another operation, Return to Home (RTH), is a safety feature that allows UAVs to automatically return to the point from which they took off under certain (or emergency) conditions. RTH feature significantly increases the flight safety of UAVs [33]. The RTH feature is automatically activated when the connection between the UAV and the controller is lost or the battery drops below a certain level, ensuring the UAV can land safely. Additionally, some RTH systems can detect obstacles and avoid collisions.

SLAM algorithms are also used to ensure the safety of UAVs. They allow the aircraft to determine its location by mapping its surroundings in situations where the global positioning system (GPS) is insufficient or disabled.

Recent studies in the literature reveal that [34] analyzed large language model (LLM) architectures to enhance the capabilities of UAVs. The study suggests that LLM models can further advance the automation features and efficiency of UAVs by leveraging the potential of artificial intelligence. This, in turn, enables research efforts that aim at directly improving the safety of UAVs.

In summary, the safety of UAVs is ensured through different technologies, sensors, and algorithms These safety systems automatically recognize and detect objects/obstacles and prevent collisions without the need for human intervention.

g. Possible Future Collision Avoidance Systems for Autonomous Vehicles

Research on autonomous vehicle safety as explored in both academic literature and industry encompasses collision avoidance and warning systems. Possible collision avoidance algorithms proposed for future investigation represent critical advancements in enhancing the safety of autonomous systems. The following section outlines future research directions identified in the existing literature. The study [35] highlights that if future work focuses on optimizing edge computing to process large sensor data across operations, it will reduce latency for AV applications and enable real-time decision-making. This would increase safety by allowing faster decisions to prevent collisions in dangerous situations. The study also mentions that future work should focus on improving simulation accuracy because differences in simulation and real-world environments pose difficulties for machine learning used in AVs.

In addition, the integration of artificial intelligence and EBS is used in autonomous vehicles to prevent collisions with different perception and decision-making mechanisms. The development of the safety of autonomous vehicles is directly proportional to the development and widespread use of these systems. For this reason, in future studies, many innovative systems can be developed, such as multi-modal detection systems (a weather-independent object recognition system by combining different technologies such as sensors and cameras), Vehicle-to-Infrastructure (V2I) Communication (providing communication between vehicles and the external environment such as traffic lights and road sensors and detecting potential dangers in advance).

5. Integration of LLMs in human-robot interaction

The integration of Large Language Models (LLMs) into human-robot interaction (HRI) has opened new avenues for enhancing the capabilities of robots in understanding and interacting with their environment and humans. This section explores the applications of LLMs in three key areas: (i) description of the environment in natural language, (ii) issuing commands to robots using natural language and (iii) applications of LLMs in humanoid assistive robots.

a. Using Large Language Models to Describe the Environment in Natural Language

Robots working in new environments often create maps that include detected obstacles. This process usually involves Simultaneous Localization and Mapping, where sensors like LiDAR or depth cameras help generate a spatial map of the surroundings. However, traditional SLAM focuses mainly on the shape of the space and doesn’t explain much about the objects within it.

By integrating perception modules utilizing sensor data, robots can go beyond basic obstacle detection. For example, object detection and segmentation algorithms enable the robot to identify and classify certain objects within its field of view. This information can enhance the robot’s spatial representation, allowing it to distinguish between different types of obstacles such as furniture, walls, or people.

Large Language Models take this capability further by transforming raw sensor data into detailed natural language descriptions. When applied to visual data from cameras, LLMs can provide context-rich descriptions of significant elements in the environment. For instance, an LLM-powered system can interpret and articulate that a room contains a sofa, a coffee table, and a television, thereby indicating it is likely a living room [36]. By generating this semantic understanding, the robot can create a "semantic map" of its environment, which links spatial locations with descriptive attributes. This semantic awareness allows robots to comprehend not only what objects are present but also the functional purpose of a space, such as recognizing a room with a sink and stove as a kitchen [37]. Such detailed mapping facilitates more intuitive interactions between humans and robots, paving the way for enhanced task planning and decision-making.

b. Natural Language Command Execution

With a semantically rich map of its surroundings, a robot becomes capable of responding to natural language commands issued by a human operator. Unlike traditional pre-programmed commands, which require precise syntax, LLM-powered robots can interpret more flexible and context-aware instructions. For example, a wheeled robot navigating an outdoor environment could be directed to “park near the red building” leveraging its semantic understanding to identify and act upon the specified location. Similarly, an indoor service robot could be asked to “bring me the book from the table” requiring it to recognize the specified objects and their relationships [38].

The ability to infer relationships between objects further simplifies command interpretation. For instance, when a human says, “I want to go to sleep; can you help me?”, then the robot can deduce that the appropriate action involves guiding the user to the bedroom - a space characterized by the presence of a bed. This contextual reasoning relies on the LLM’s capacity to understand both the user’s intent and the functional purpose of objects and spaces within its semantic map.

LLMs also play a crucial role in speech-to-text transcription and voice generation, which are essential for voice-based communication with robots. This allows users to interact with robots using spoken commands, enhancing the user experience and making robots more accessible to a wider range of users [39].

c. Applications of LLMs in Humanoid Assistive Robots

LLMs have significant potential in enhancing the capabilities of assistive robots, particularly those designed to aid elderly or disabled individuals. For instance, robots equipped with LLMs can assist with daily tasks such as feeding, dressing, or providing companionship. These robots can understand and respond to natural language commands, making them more user-friendly and accessible to those who need assistance [40].

Moreover, LLM-powered robots can potentially serve as cooks or household assistants, capable of preparing meals or performing chores based on voice commands. This application not only improves the efficiency of household tasks but also enhances the independence of individuals who may struggle with these activities due to physical or cognitive limitations [41].

In addition to these domestic applications, LLMs can be integrated into robots designed for healthcare settings. For example, they can aid patients at the bedside, monitor their condition, and provide personalized care instructions based on real-time data analysis. The versatility of LLMs in HRI opens up numerous possibilities for improving care delivery and enhancing the quality of life for individuals in need of assistance.

Beyond caregiving and cooking, humanoid robots with LLMs can support a wide range of activities, including education, customer service, and hospitality. For example, in educational settings, they can act as interactive tutors, explaining concepts and answering questions conversationally. In customer-facing roles, they can provide detailed information about products or services, making interactions more engaging and personalized.

In summary, the integration of LLMs into humanoid robots significantly broadens their range of applications, making them invaluable tools in diverse scenarios where natural and intuitive communication is essential.

6. Integration of AI with V2X systems in autonomous vehicles

Autonomous driving (AD) is anticipated to bring significant benefits to human society in the future 6G vehicular ad hoc networks (VANETs) [42]. Typically, dissemination of real-time traffic information (e.g., HD map, parking guidance) is necessary to support emerging time-sensitive AD services (e.g., remote driving, metaverse). Most existing works [43] [44] investigate the hybrid data dissemination with vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) transmissions among roadside units (RSUs) and vehicles. However, the burden and contention of data dissemination in 6G VANETs would be much heavier with the increasing number and more stringent requirements of emerging AD services, which brings significant challenges for existing data dissemination methods. On the other hand, semantic communication has recently shown significant advantages [45]. Unlike traditional communication, which focuses on bit accuracy, semantic communication concentrates on holistic meaning delivery. Semantic communication can significantly reduce communication traffic, integrated with an artificial intelligence (AI) model-enabled semantic encoder/decoder. However, in future VANETs with massive resource-limited vehicles, calculating complete semantic model updates on vehicles will lead to high computation costs. An energy-efficient semantic communication architecture is necessary for sustainable AD service [46]. Most recently, digital twin (DT) is a promising paradigm for 6G VANETs architecture innovation [47], [48]. In the DT-based 6G VANETs, each vehicle owns a synchronized twin object (vehicle twin) on the mobile edge computing (MEC) server for intelligent state analysis and decision-making. These twin objects on MEC servers construct the DT networks via twin-to-twin (T2T) communication. In most cases, T2T occurs as inter-process communication (IPC) [49] between vehicle twins within the same MEC server, which is much faster and more stable than V2V and V2I communications. Considering this characteristic, we leverage the DT networks to disseminate data parallel to physical VANETs. In this way, the transmission contention in physical VANETs is mitigated, and the dissemination efficiency can be improved.

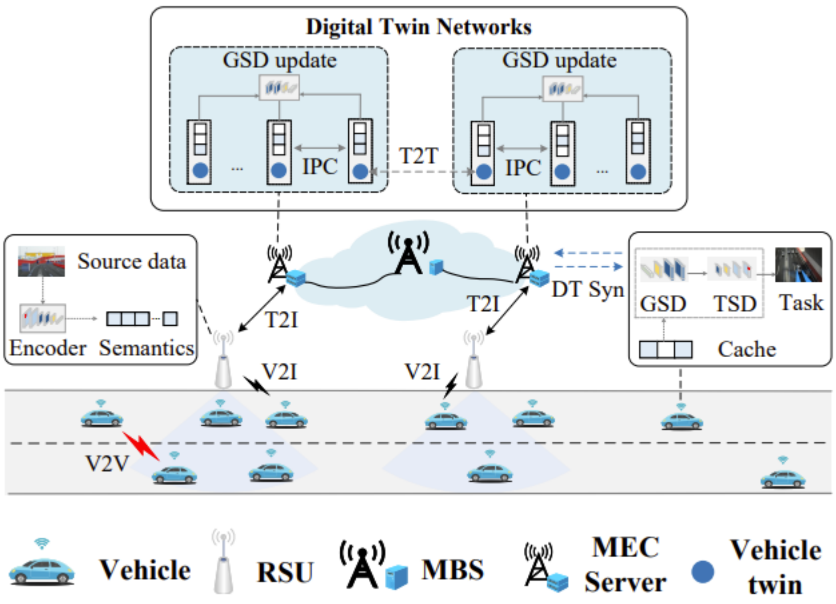

Fig 3: DT-based semantic dissemination architecture for 6G VANETs.

a. System architecture and system model

DT-based Semantic Dissemination Architecture

As shown in Fig.3, three types of entities exist in the proposed DT-based semantic dissemination architecture: RSU: The RSUs are the source of AD service data, which have enough storage but limited computation resources. Before data dissemination, each RSU encodes the service data into semantic chunks with an AI model. The wireless communication radius of RSUs is limited, and they can only disseminate semantic data to the vehicles within their range. Each RSU builds a twin-to-infrastructure (T2I) link connected to a MEC server to access the DT networks. Vehicles: The vehicles can exchange semantics with neighbor RSUs, MEC servers, and others by onboard semantic encoders/decoders. For energy saving, we further divide them into (i) the general semantic encoder/decoder (GSD) for recognizing the common semantic characteristic and (ii) the task-oriented semantic encoder/decoder (TSD) for identifying the specific semantic of AD task on each vehicle. A vehicle only reports the local TSD loss to the MEC server through vehicle twin.

The MEC server uses the collected TSD loss to update the GSD federally and return it to each vehicle. MECServer: An MEC server contains multiple vehicle twins: the vehicle twin can communicate with its physical vehicle, other vehicle twins, or the connected RSU. Besides, a macro base station (MBS) is linked to each MEC server for central analysis and decision-making. The workflow of the proposed architecture is shown in Fig. 4.

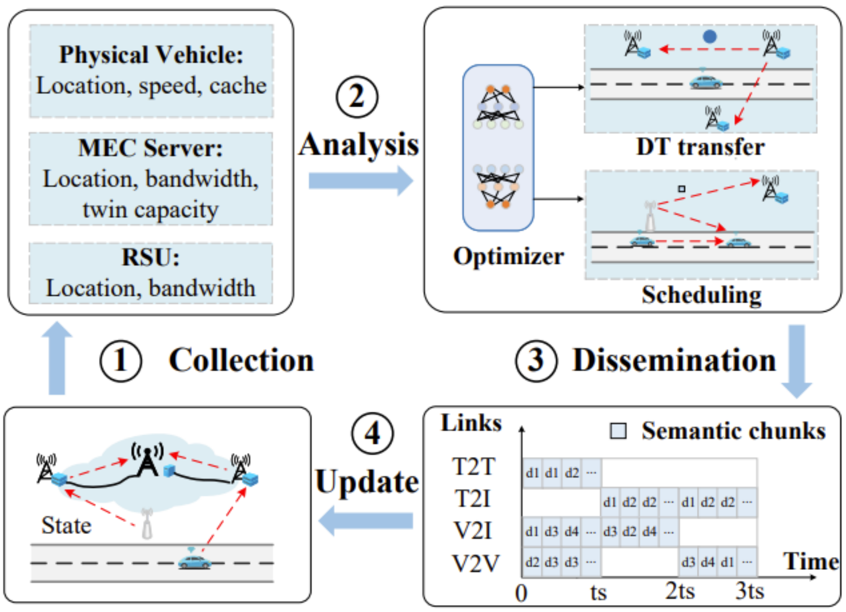

Fig. 4. Workflow of the proposed semantic dissemination architecture

In the information collection stage, MBS collects the state of physical vehicles, MEC servers, and RSUs. As for the analysis stage, the central MBS trains an optimizer for DT transfer and semantic transmission scheduling. In the dissemination stage, the MBS makes decisions for the involved entities in each time slot. The environment is updated and transits into the next cycle when the dissemination stage is over.

The advantages of our proposed architecture are three-fold:

1) Dissemination burden reduction: The entities exchange information with each other by semantic communication, which can reduce the disseminated data volume.

2) Transmission contention alleviation: For the sake of contention avoidance in 6G homogeneous networks, a physical vehicle cannot communicate with RSU and neighbor vehicles at the same time. However, when the physical vehicle is occupied, the vehicle twin can still request semantic chunks from RSU or other vehicle twins. Meanwhile, semantic dissemination in DT networks tends to be faster and more stable due to IPC. When the physical vehicle is free or drives off the range of RSU, it can continue to synchronize semantic chunks from the vehicle twin. Thus, the physical transmission contention is alleviated and improved dissemination efficiency.

3) Energy saving: The semantic encoder/decoder of vehicles is divided into GSD and TSD. Vehicles only calculate local TSD updates and report them to vehicle twins for federal GSD updates, which saves energy costs for on-vehicle GSD updates.

b. Performance evaluation

Experiments were conducted on a computer with 2 Intel® Xeon® 5217 CPUs (3.0GHz), an NVIDIA RTX 3090 GPU, 128GB DDR4 RAM, and a 12TB disk. For the semantic communication simulation, a 4-layer convolutional neural network (CNN)-based general semantic encoder/ decoder (GSD) and a 6-layer transformer-based task-oriented semantic encoder/decoder (TSD) on the Cityscapes dataset were trained. The Cityscapes dataset focuses on the semantic understanding of urban streets for the VANETs scenario. We referred to OpenStreetMap for real-world road information and select a rectangle area around our campus in Shanghai, China. Besides, the 5G signal distribution based on the dataset provided by Shanghai Unicom, was used and all the RSUs and MEC servers were deployed within the signal coverage. The simulation of urban mobility (SUMO) was used to generate the vehicle mobility traces. Finally, a PPO-based agent on the Pytorch platform was deployed to interact with the simulated VANETs environment. The key simulation parameters are summarized in Table. I. PD3 was compared with the other three typical data dissemination schemes listed below.

- Random data dissemination scheme: The random dissemination scheme is a typical benchmark method. It randomly determines whether to adopt V2I or V2V transmission for requesting vehicles in each time slot.

- Offline hybrid data dissemination (OFDD) scheme: The OFDD is one of the state-of-the-art data dissemination schemes proposed by Yang et al. in [44]. It prioritizes the most beneficial V2V transmission and then chooses V2I transmission if feasible. This was slightly modified to make it suitable for solving the problem in this report.

- Pure PPO scheme: A pure-PPO learning scheme was set up for comparison to test whether the DT-aided data dissemination scheme brings additional advantages.

Parameter	Value	Parameter	Value
RSU coverage	150 m	Noise power	$10^{-16}W$
MEC coverage	300 m	Recoverable ratio η	0.7
Vehicle coverage	100 m	RSU bandwidth	40Mb/s
Service chunks	20	MEC bandwidth	100Mb/s
Vehicle bandwidth	10Mb/s	Vehicle power	20dBm
RSU power	30dBm	MEC power	40dBm

Table I: Key Simulation Parameters

a. Experimental analysis

The proposed semantic dissemination architecture's data volume and energy consumption were first investigated. As shown in Table. II, compared with the traditional JPEG2000-based [50] data encoding method, the CNN and transformer-based semantic encoding method disseminates fewer data bits while keeping the same minimum AD task accuracy. On the other hand, our proposed semantic model update method consumes lower energy costs than the complete on-vehicle model update scheme.

Disseminated data volume (Compared to JPEG2000)		**Energy consumption (Compared to on-vehicle update)**	
Minimum accuracy	Disseminated bits reduction (%)	Number of vehicles	Computation reduction (%)
0.80	**22.3**	100	**17.1**
0.85	**7.3**	200	**18.4**
0.90	**1.4**	300	**19.0**

Table II: Evaluation of the proposed Semantic Dissemination architecture based on the Cityscapes Dataset.

Fig. 5 (a)-(b) shows the performance of the proposed PD3 scheme with the number of training timesteps and the attributes of MEC servers. In Fig. 5 (a), the episode reward of the pure PPO scheme and our proposed PD3 scheme are compared. The density of deployed MEC servers for PD3 is set to 4 km2, the maximum twin capacity Pm for each MEC server is 3, the number of vehicles requested during an episode is 800, and the average speed of vehicles is 40 km=h. As shown in Fig. 5 (a), the PD3 scheme achieves 74.35 % higher episode reward than the pure PPO scheme on average, which showed the advantage of DT-aided dissemination. Fig. 5 (b) describes the reward of the proposed PD3 schemes with the density of MEC servers under different twin capacities. As the density and computational capacity of MEC servers increase, the average reward exhibits a corresponding upward trend.

In Fig. 6 (a)-(b), shows the impact of the quantity and velocity of requesting vehicles on normalized semantic dissemination delay and dissemination ratio. According to Fig. 6 (a), the normalized semantic dissemination delays increase for all schemes as the average vehicle velocity increases. At the same time, the proposed PD3 outperforms other schemes and achieves 18.36% lower dissemination delay than the scheme on average. As shown in Fig. 6 (b), our proposed PD3 scheme outperforms other schemes and achieves a 4.51% higher semantic dissemination ratio on average than the OFDD scheme. When the number of vehicles is less than 400, the semantic dissemination ratio keeps increasing with the number of vehicles due to more frequent V2V transmission. However, when the number of vehicles further increases, the dissemination ratio decreases because of the twin capacity limit of MEC servers [51].

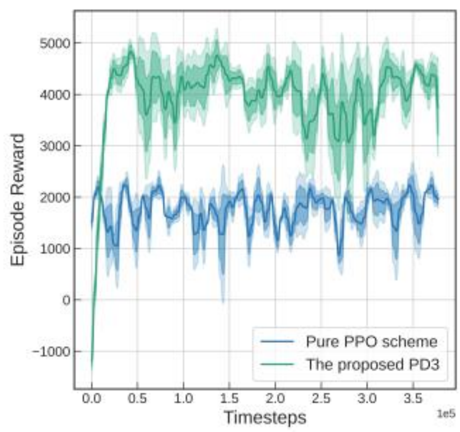

Fig. 5(a): Reward V.S. Timesteps

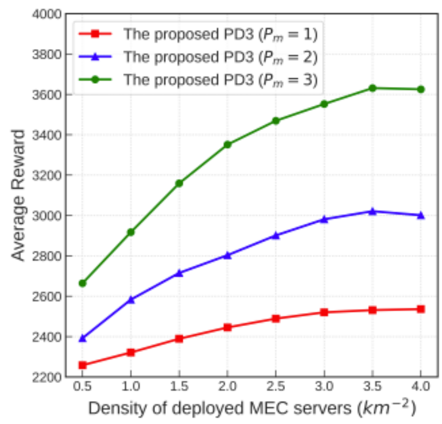

Fig. 5(b): Reward V.S. MEC server density

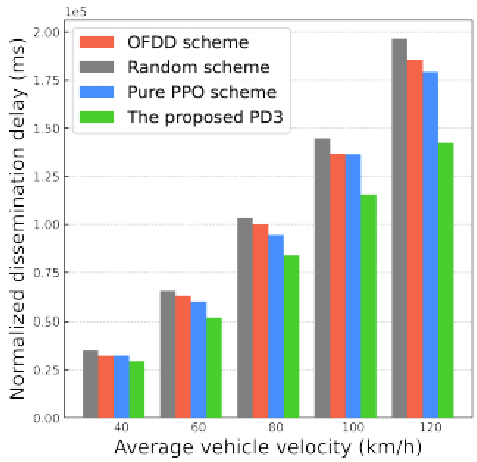

Fig. 6(a): Delay V.S. Vehicle velocity

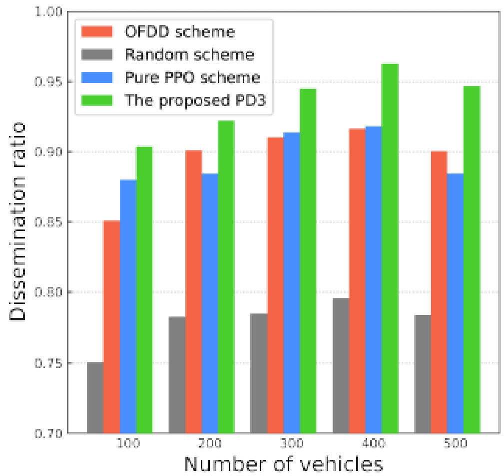

Fig. 6(b): Ratio V.S. Number of vehicles

7. Conclusions

The development of artificial intelligence and data-driven electronic systems significantly impacts the safety of autonomous systems, particularly in the robotics and automotive sectors. The integration of deep learning techniques, sensor data analysis, and language models enhances real-time diagnostics, predictive maintenance, and system event analysis. In robotics and autonomous vehicles, advanced environmental perception methods—such as object detection, image segmentation, and multi-sensor data fusion—enable more precise and reliable safety system operations. Autonomous safety systems play a crucial role in accident prevention, incorporating behavior prediction of road users, automatic emergency braking, and collision avoidance mechanisms. The advancement of language models opens new possibilities in human-robot interaction, allowing for natural communication and intuitive command execution. Meanwhile, the application of artificial intelligence in vehicle-to-everything (V2X) communication systems supports efficient data management and optimization of decision-making processes. Despite significant progress, further research should focus on improving AI model transparency, increasing computational efficiency, and integrating hybrid methods that combine classical engineering approaches with machine learning techniques. Ultimately, the growing role of artificial intelligence in safety systems contributes to enhancing the reliability of autonomous systems, and continued development in this field could lead to groundbreaking transformations in modern technologies.

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N.K. Ł.S. P.B J.D. (IITiS) were responsible for Literature Review, Selection, and Analysis in Sections 2, 3, 4 and 5. F.F. S.M. (DME) worked on Literature Review and Interpretation in Section 6. F.T.-M. (University of Wolverhampton) supervised the review process and contributed to the final synthesis.

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Option 3, Lisbon;

Verapaz (click to view)

Map to show distance and directions (click to view)