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Review

Advanced Sensor Technologies in CAVs for Traditional and Smart Road Condition Monitoring: A Review

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Abstract: This paper explores new sensor technologies and their integration within Connected Autonomous Vehicles (CAVs) for real-time road condition monitoring. Sensors like accelerometers, gyroscopes, LiDAR, cameras, and radar that have been made available on CAVs are able to detect anomalies on roads, including potholes, surface cracks, or roughness. This paper also describes advanced data processing techniques of data detected with sensors, including machine learning algorithms, sensor fusion, and edge computing, which enhance accuracy and reliability in road condition assessment. Together, these technologies support instant road safety and long-term maintenance cost reduction with proactive maintenance strategies. Finally, this article provides a comprehensive review of the state-of-the-art future directions of condition monitoring systems for traditional and smart roads.

Keywords: advanced sensors; Automated Connected Vehicles (CAVs); road monitoring systems; pavement defects; smart roads

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1. Introduction

Road condition monitoring is essential to enhance traffic safety and prevent accidents. According to the World Health Organization, about 1.35 million people die annually from road traffic crashes [1], many of them because of bad road conditions: potholes, wet or icy surfaces, and debris. Thanks to the advanced sensor technologies in Automated Connected Vehicles (CAVs), these hazards can be detected and signals issued to the driver, significantly reducing the chances of an accident. An autonomous vehicle depends on accurate information about road conditions for modifications in driving behavior, which contributes to improving control and stability on various surfaces. According to the National Highway Traffic Safety Administration (NHTSA) report, almost 22% of vehicle crashes in the United States are attributed to road-condition-related issues; this means that effective monitoring systems are critical for this technology [2].

In addition to guaranteed safety, monitoring the road conditions contributes much to traffic efficiency and maintenance practices. Real-time monitoring allows traffic to be rerouted through traffic management systems from the areas of trouble; thus, reduced congestion is achieved with better traffic flow. According to the Texas A&M Transportation Institute, congestion costs the U.S. economy over USD 166 billion annually from lost productivity and fuel waste [3]. Informed by continuous monitoring, road maintenance can be efficient enough to extend the lifespan of infrastructure and simultaneously cut maintenance costs. For example, the Federal Highway Administration reports that preventive maintenance can save up to USD 10 in future repair costs for every USD 1 spent [4]. Prioritization of repairs with the correct data will allow for the proper allocation of resources in municipalities, ensuring better and safer travel for everybody.

The concepts of "sensor technologies" and "road monitoring" have been of great interest for many years now, as highlighted by the Google Trends time series (Figures 1 and 2).

However, road monitoring has seen growing interest starting from 2021 (Figure 2). Instead, the concentration of "connected vehicles" has undergone ever-increasing growth in the last decade, starting from a score of 20% in 2014 up to a score of 100% in 2024 (Figure 3). These time series show a generalized community interest in new mobility technologies and the application of sensors to road monitoring.

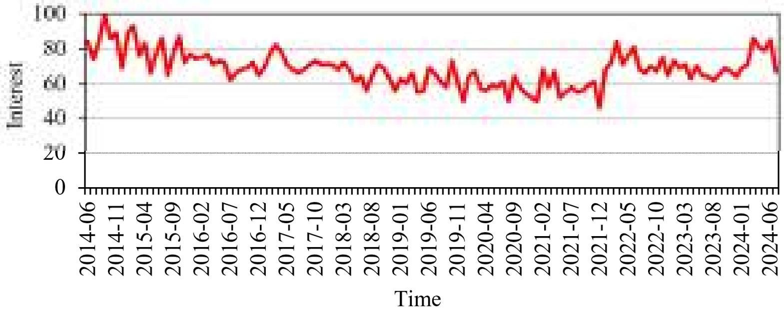

Figure 1. Time series of Google Trends searching interest, years 2014–2024, for "sensor technologies".

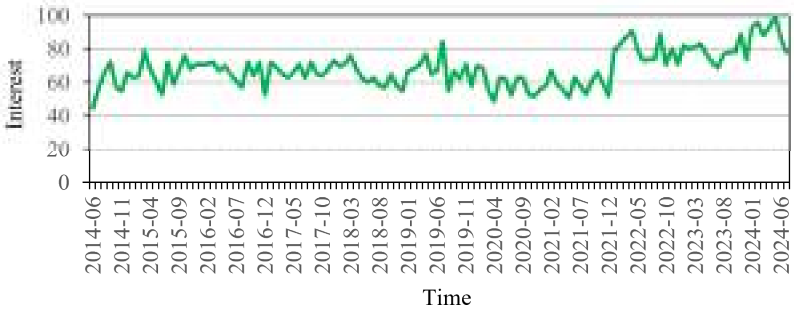

Figure 2. Time series of Google Trends searching interest, years 2014–2024, for "road monitoring".

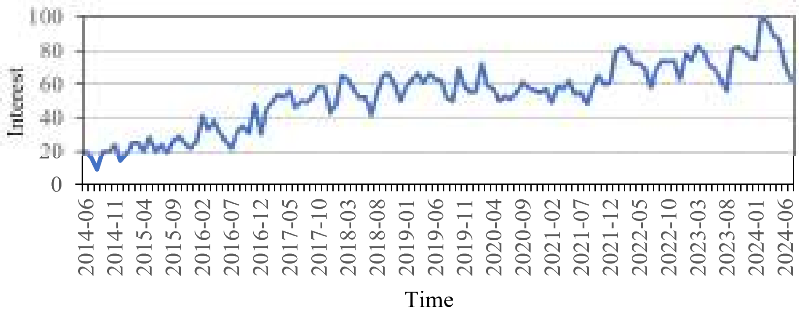

Figure 3. Time series of Google Trends searching interest, years 2014–2024, for "connected vehicles".

The main contributions of this work are fourfold. It will first explain what a connected vehicle is and its place in today's transportation system. Second is a critical review of the various sensor technologies placed on connected vehicles for monitoring road conditions; this includes details on how the sensors could be applied to intelligent transportation systems, enabling better road safety, traffic efficiency, and infrastructure maintenance. Third, this study delves into the practical applications of sensor technologies such as pothole detection, surface classification, weather impact assessment, crack detection, road roughness measurement, lane detection, and traffic sign recognition. This further helps to establish how applications improve real-time road monitoring, leading to proactive maintenance and efficient traffic management. Finally, this work elaborates on the challenges and limitations in deploying sensor technologies such as sensor accuracy, data fusion, real-time processing, power consumption, and regulatory issues. This paper discusses the possible solutions and directions to solve these challenges, setting a future path for developing such road condition monitoring systems and their incorporation into practical and sustainable implementations within connected vehicles.

2. Terminology and General Concepts

Connected vehicles: The term connected vehicles, which are also sometimes called intelligent or smart vehicles, refers to an automobile that is equipped with internet connectivity and a range of different sensors, hence allowing it to communicate with others of its kind (vehicle-to-vehicle or V2V), with infrastructure (vehicle-to-infrastructure or V2I), and with everything else—including pedestrians and network services—through the vehicle-to-everything or V2X concept. These vehicles are provided with advanced communication technologies of dedicated short-range communications (DSRC) or cellular networks—4G/5G and satellite systems—to share real-time data among each other and increase the driving experience and safety [5]. When brought into the IoT and edge computing frameworks, CAVs are further integrated for the desired development of intelligent transportation systems. They enable policy-making at a global traffic level and decision-making at the local level to increase traffic flow and reduce travel times [6,7]. The functionalities of connected vehicles are numerous and multifaceted but the most important ones include the following.

Real-time traffic information: Real-time traffic information on connected vehicles is one of the critical steps in transportation technology toward safe and efficient systems. Realized through the technologies of V2V (vehicle-to-vehicle) and V2I (vehicle-to-infrastructure), drivers receive real-time traffic data to adjust their routes automatically, reducing congestion. In this context, integrating such data for real-time traffic management ensures precise, accurate, and timely decision-making toward mitigating traffic jams and optimizing travel time. Research has shown that these systems can significantly increase traffic flow efficiency and decrease road transportation's environmental burden by reducing delay times and fuel consumption [8–10]. Further, real-time traffic information has significant economic benefits because lower congestion implies lower transportation costs and higher productivity [11]. With the maturation of technology, further extensive optimization in traffic and urban mobility management becomes more feasible than ever.

Enhanced safety features: Enhanced security characteristics are realized in the connected vehicles through the sharing of real-time information with other vehicles (V2V), infrastructure (V2I), pedestrians (V2P), and networks (V2N). This is through the use of V2X—vehicle-to-everything communication technologies. The widespread communication ensures maximized situational awareness and detection of hazards, therefore averting accidents and increasing road safety. V2V communications mean data sharing between vehicles associated with critical information such as speed, position, and direction, which is highly relevant for crash avoidance [12]. Connected vehicles also promise enhanced pedestrian safety through V2P communications, which makes the drivers aware of the movement of a pedestrian even outside his line of sight, further reducing the risk of accidents in urban environments [13,14]. Equally important is the optimization of traffic flow and reduction in congestion to further reduce risks of accidents—such as the associated sudden stops and erratic driving behaviors—through intelligent traffic management via V2I communication. In other words, the changes clearly prove how connected vehicle technology is transforming road safety in terms of smart and vastly safer transportation systems [14,15].

Remote diagnostics and maintenance: Based on advanced telematics and IoT technologies, remote diagnostics and maintenance for connected vehicles carry out real-time monitoring and management of the vehicle's health and performance. This helps to read the possibility of problems beforehand, thereby reducing failure cases while optimizing the maintenance schedule. Recent studies have shown that through data collected from various vehicle sensors, these remote diagnostic systems can predict possible failures and schedule maintenance as needed to enhance vehicle uptime and reliability even more [16,17]. Further research shows that machine learning algorithms are embedded in the analysis of big data that emanates from such connected vehicles for more accurate diagnostics and predictive maintenance [18,19]. Recent research has proven that these systems, due to their increase in operational efficiency, cut costs significantly by minimizing unscheduled maintenance and downtime [20]. These advanced studies depict a new change in the automotive industry for efficient and reliable transportation.

Autonomous driving support: Real-time data processing, using machine learning algorithms and communication networks, enhances independent driving support for autonomous vehicles by allowing them to operate in complex environments and be able to interact with all the surrounding infrastructure. Recent studies found that autonomous driving systems enable the use of advanced sensors and real-time data analytics to enhance situational awareness and safety [21–23]. Furthermore, research emphasizes the contribution of deep learning and artificial intelligence to improving accuracy and dependability in autonomous navigation systems [24,25]. Further studies also show that V2X (vehicle-to-everything) communication frameworks play a vital role in enabling autonomous vehicles to interact with traffic lights, other vehicles, and pedestrian systems for a safe, integrated driving environment [25,26]. In sum, these innovations in automated driving help underline the transformable effect of connected vehicle technologies in modern transport.

Infotainment and convenience services: The connectivity systems in connected vehicles are taking the experience of driving to an entirely new, different level by pushing the bars of comfort, entertainment, and communication mobility to unimaginable levels. These real-time data and cloud connectivity systems give drivers and their passengers a complete suite of offerings, from streaming entertainment and navigation help to seamless integration for smartphone services. The basis of these systems lies in recent research that brings modern data analysis and machine learning for the sake of individualized content and recommendations based on the user's preferences and driving patterns. More research is inclined toward robust communication networks and the Internet of Things, thus making these services reliable and secure, with users enjoying seamless connectivity with updates up to the minute [6,27–29]. Even more, new research insights show the integration of the infotainment systems into the greater infrastructure of smart cities in order to bring the experience of context-aware information and services [30,31]. All these advances ensure that the driving experience is pleasurable, convenient, and utterly connected, fitting with the developments happening in the automotive industry.

A connected vehicle is a significant element in advanced transportation systems that seek to improve road safety and traffic efficiency and reduce environmental footprints. Connected vehicle applications within intelligent transportation systems will allow for more harmonized and efficient road operations. Another example is being able to optimally time the traffic signals and tune the speed limits dynamically by the real-time traffic situation, which would subsequently significantly reduce traffic congestion and associated emissions using connected vehicles. Citing Jing et al. 2017, it reduces delays and fuel consumption by 5–10% [32]. Additionally, connected vehicles contribute to a safer transport ecosystem by providing the potential for more timely and informed interventions in safety-critical situations. Connected and automated vehicle (CAV) technologies are projected to reduce crashes by approximately 57.97% [33]. Moreover, they are necessary to drive smart cities: integrated data from all possible sources, of which one is connected vehicles, help cities improve urban mobility and the quality of life [34].

In summary, connected vehicles will have advanced functionalities. They will be integrated into modern transportation systems, including Smart roads, transforming the individual driving experience and contributing to more widespread societal goals of safety, efficiency, and sustainability.

3. Review of Sensor Technologies in CAVs

Connected and Automated Vehicles (CAVs) are based on different advanced sensor technologies (cf. Table 1 and Figure 4) to control the traffic environment and achieve safe operation. The suite of sensors used is likely to comprise accelerometers, gyroscopes, LiDAR cameras, radar, and others helping detect pavement anomalies like potholes, cracks, and rough surfaces based on real-time data processing. This section will not address the functioning of every sensor in great detail but rather summarize its roles and functions within CAVs with an overall emphasis on safety and environment monitoring.

Table 1. Review of sensor technologies.

Sensor Type	Functionality	Application
Accelerometers	Measure forces of acceleration, vehicle dynamics, motion	Electronic stability control, airbag deployment, predictive maintenance
Gyroscopes	Determine angular velocity, navigation stability, control	IMUs in navigation systems, stability control, ADAS
LiDAR	Create high-detail environment maps, advanced object detection	Collision avoidance, navigation, urban environments
Cameras (Optical Sensors)	Visual information, navigation, object perception, decision-making	Object recognition, lane detection, traffic sign recognition, traffic flow measurement, pavement distress analysis
Radar Sensors	Object detection and tracking, all-weather operation	Adaptive cruise control, collision avoidance
Ultrasonic Sensors	Short-range detection, parking aid, collision mitigation	Urban areas, slow-speed vehicle detection
Infrared Sensors	Object detection and monitoring in low light/adverse conditions	Enhanced detection at night or in fog
Microphones (Acoustic Sensors)	Noise cancellation, detection of vehicle proximity and obstacles	ADAS, hands-free functionality, voice commands
Temperature Sensors	Regulate thermal conditions for proper operation and safety	Engine, battery, cabin temperature management
Humidity Sensors	Detect moisture, prevent corrosion/mold/electrical failures	Battery health, HVAC system maintenance
Magnetometers	Measure magnetic fields for guidance and orientation	Reliable navigation data, urban canyon environments
Piezoelectric Sensors	Convert mechanical energy into electrical signals, monitor vibrations/pressure	Energy harvesting, real-time monitoring, predictive maintenance
Strain Gauges	Measure mechanical strain, monitor stress and deformation	Chassis, suspension systems, gearbox monitoring
Vibration Sensors	Monitor mechanical and road-induced vibrations	Engine, suspension, drivetrains monitoring
GPS (Global Positioning System) Sensors	Collect location data, navigation, fleet management	Real-time tracking, route optimization
Electromagnetic Sensors	Object detection, collision avoidance, autonomous navigation	Enhanced detection in varied driving conditions
Proximity Sensors	Identify proximity of entities to minimize collisions	Parking assistance, blind-spot detection
Tire Pressure Monitoring Sensors	Send real-time data of tire pressure, prevent blowouts	Optimize vehicle functionality, tire maintenance

The bottom line is, vehicle dynamics—acceleration forces/vibrations and motion—need to be monitored. This makes it highly compact and precise with the advantage of MEMS (Micro-Electro-Mechanical Systems) technology, which reduces power consumption. For example, the systems responsible for the electronic stability control and predictive maintenance of vehicles are dependent on a fast H2H bus to enhance performance and comfort levels [35–37]. Another important sensor type, the "gyroscope", measures angular velocity and helps maintain an accurate positioning of the vehicle, including support through auto-follow features (by twisting your neck) and stabilization. These sensors, particularly those based on MEMS devices [38], are part of systems such as inertial measurement units (IMUs) to improve navigation and safety, specifically in critical situations like accidents [39,40].

Figure 4. Main sensors used in CAVs.

LiDAR sensors offer detailed 3D environmental maps of current market demands, which are necessary for object detection and collision avoidance in complex environments as well as navigation. These complement other sensors, especially when vulnerable vision-based sensors fail—e.g., in the presence of poor lighting or occlusion [40–43]—by emitting laser beams to form high-definition maps. Cameras achieve the same with visual information, providing object recognition abilities as well as identifying everything from lanes to other objects around them. Nevertheless, they can be impaired by adverse weather conditions and, therefore, operate in a more performant way when combined with the use of other sensor systems such as radar or LiDAR [41,44–47].

Radar sensors detect objects reliably under all weather conditions as they determine distances and speeds in driving directions by radio waves. Radar is also more useful when environmental factors like rain and fog decrease the effectiveness of other sensors. It is used commonly in functions like adaptive cruise control, blind spot detection, and collision avoidance. Ultrasonic sensors, on the other hand, are typically used for short-range detection like parking assistance and slow-speed collision mitigation. Practical and low-cost sensors [46,48–51] have been implemented in urban scenarios.

Object detection is vital and can be achieved more accurately using infrared sensors compared to traditional sensors, especially in low-light conditions or advancing weather. Infrared sensors detect thermal radiation and thus can work well at night or in fog. Together with algorithms such as YOLO-FIRI, these sensors enable superior vehicle detection and safety when used in a larger sensor fusion context of CAVs [52–54]. A lot of this work is now centered around the use of sound waves for obstacle identification and proximity assessments through acoustic sensors or microphones. They are also employed for applications providing hands-free features and voice-activated systems, improving the safety of drivers and decreasing distraction between operations [55,56].

Temperature and humidity sensors regulate the thermal and moisture conditions of different parts like the engine and battery in vehicles. In harsh environment applications, they provide extra protection against overheating and corrosion or failure due to electrical breakdown through the integrated sensors. Advanced CMOS-based temperature sensors are integrated into CAVs and their enhancements for reliable, predictive maintenance [57–62]. Magnetometers measure a magnetic field and are necessary for navigation, particularly when GPS is weak or unavailable [63–65].

The third type of sensor monitors the mechanical data like vibrations, stress, and pressure on the vehicle components, which includes piezoelectric sensors and strain gauges. By using these sensors, real-time structural health monitoring and predictive maintenance can be performed that helps prolong vehicle life and reduce unscheduled repairs. Energy harvesting is one of the most important concerns in CAVs, and piezoelectric sensors are capable devices for this goal [66–73]. These are further complemented by vibration sensors, capable of detecting incipient mechanical failures in critical components such as engines and drivetrains [74,75], whereas GPS-enabled location tracking becomes useful for navigation and fleet management operations, providing real-time positional data with a high degree of precision [76] or broad accuracy range, respectively [77]. They provide real-time location and smart routing, which improve transport efficiency and security. Moreover, the integration of GPS with inertial measurement units makes it even more accurate, particularly in places like urban canyons that face signal obstruction. Further, together with VIA communication devices, GPS sensors are also used to regulate traffic flow and avoid occurrences by enabling critical position data exchange between vehicles (V2X) [12,77,78].

Electromagnetic sensors contribute to CAV safety by detecting object distances, enabling collision avoidance, and supporting autonomous navigation. These sensors are increasingly being integrated with LiDAR and radar to enhance detection performance under various conditions. Like GPS, electromagnetic and proximity sensors are also integrated with V2X systems, boosting situational awareness and traffic flow by sharing real-time information between vehicles and infrastructure. Proximity sensors, using ultrasonic, infrared, or capacitive technologies, ensure close-range object detection, crucial for tasks like parking assistance and blind-spot detection. Tire Pressure Monitoring Sensors (TPMS) further enhance vehicle safety by continuously monitoring tire pressure, preventing accidents caused by underinflated tires and improving fuel efficiency [26,47,54,60,79–83].

4. Road Condition Monitoring

4.1. Data Processing Techniques and Algorithms for Road Condition Monitoring

Road condition monitoring is considered one of the most important subjects in intelligent transportation systems concerning CAVs. When integrated with advanced techniques and algorithms, the availability of advanced sensor technologies allows for online road condition monitoring and analysis. This section focuses on the techniques and algorithms used to process the data from the sensor for the assessment and accurate monitoring of road conditions (Table 2).

A. *Signal Processing Techniques*

(a) Filtering and noise reduction are significant operations for the improved monitoring of road conditions by CAVs. Advanced filtering techniques, such as Kalman filters, help minimize the effect of sensor noise and environmental disturbances to increase real-time data reliability [84]. Several important improvements have been noted using these methodologies for detecting road anomalies, leading to better safety and operational efficiency [85]. Integration with machine learning-based noise reduction algorithms would refine the data by detecting relevant signals against background noise. Such advanced filtering techniques are required to make autonomous vehicle systems robust under different road conditions [86];

(b) Feature extraction: More recently, the process applied to CAV monitoring is based on feature extraction—road anomaly detection and classification. It involves potholes, cracks, surface wear, etc. The techniques applied include the dimension reduction and feature extraction of meaningful patterns out of large datasets using Principal Component Analysis (PCA) and Independent

Component Analysis (ICA) [87]. Any of the given deeper learning methods, notably Convolutional Neural Networks, will perform very well for this kind of work because of their feature extraction power, which can accurately recognize irregularities in the road surface more or less in real-time [88]. These techniques allow autonomous vehicles to make intelligent decisions in adaptation to dynamically changing conditions of the roads for safety and smooth driving experiences.

B. *Machine Learning and Artificial Intelligence*

(a) Supervised learning: Supervised learning algorithms have been utilized with SVMs and RFs through the use of labeled datasets that make it possible for the autonomous vehicle to detect the conditions of roads and make well-informed decisions. Several researchers have shown the effective use of SVMs for pothole and crack detection and high accuracy in robust diversifying textures of road classification with RFs [89,90]. Constant fine-tuning of supervised learning models ensures that autonomous vehicles react well to all types of road conditions, increasing their efficiency [91];

(b) Unsupervised learning: In detecting patterns from road condition data without labels on their datasets, unsupervised learning techniques are hence very important since labeled data might not always be available. Clustering techniques like the K-means and DBSCAN have been implemented to detect and categorize road anomalies using data collected by vehicle sensors. Research has shown K-means to be effective in classifying road surface irregularity types [92], whereas Zhao et al. (2022) have also demonstrated that DBSCAN can perform outlier detection pointing toward road damage. More recently, using autoencoders for road surface reconstruction, any new deviation from the norm can be detected [93]. An unsupervised learning approach, combined with continuous data collection, allows the autonomous vehicle to learn and adapt to new road conditions, thereby further increasing operational robustness;

(c) Deep learning: Using mainly CNNs and RNNs, deep learning has furthered road condition monitoring to the point where autonomous vehicles can make meaning from complex high-dimensional sensor data. For example, CNNs have been proven very good at feature extraction from visual inputs, and that allows great accuracy in identifying potholes and cracks on the roads [94,95]. RNNs are a type of network designed to handle sequences of data suitable for prediction of the state of the road, given historical data [96]. By fusing this knowledge with the deep learning model through real-time sensor data, self-driving vehicles constantly monitor and adapt to the changing conditions of the road, becoming safe and increasingly more efficient when actually deployed [97].

C. *Data Fusion Techniques*

(a) Multi-sensor data fusion: The sensors used in recording the road conditions for CAVs remain a crucial issue that will require initiative to improve its accuracy and robustness. Fusing the data from sources such as LiDAR, cameras, and accelerometers will give a very descriptive environment of the road. Previous work has shown that combining the LiDAR data with data obtained from cameras greatly improves the detection of anomalies on the surface [98]. The relevance of the information applied helps add more information that might help identify potholes and bumps [99]. Additionally, the sensor fusion helps reduce false positives and improves real-time decision-making [47]. Thus, the research studies above stress the importance of multi-sensor data fusion in designing an autonomous system that would work safely and efficiently under different road conditions;

(b) Contextual data integration: This has led to real-time sensor data being integrated with monitoring road conditions in CAVs, along with other contextual data, such as weather conditions and traffic patterns at any given instant, including historical road maintenance records. Indeed, recent studies showed that integrating weather data into a model greatly improves the accuracy of predicting road conditions, particularly under adverse conditions [87]. Similarly, other reports showed that integrating traffic flow information also improved predictions of road wear and potential hazards [100]. In addition, Soprayoga et al. (2020) [101] further validated the usefulness of historic maintenance records for spotting locations subject to repetitive problems [102]. This can be achieved by incorporating contextual information to give the most holistic and accurate perception of road conditions for the safe and efficient navigation of vehicle routes [103].

D. *Predictive Analytics*

(a) Time-series analysis: Probably one of the most key predictive analytics to monitor road conditions in autonomous vehicles would be time-series analysis. This provides for extracting patterns and trends from historical data, projecting these into the future, making it possible to predict road conditions. The literature has identified that ARIMA is efficient in predicting vehicle velocity and road gradient [104]; on their part, Staudemeyer and Morris (2019) explained that LSTMs are actually good models for sequential data as they capture long-term temporal dependencies. They introduced a variable-neuron-based LSTM for enhanced modeling of long-term dependencies that can be applied directly or with minor modifications to road-wear data modeling [101]. Incorporated time series analysis and real-time sensor data give added accuracy to prediction in road conditions, hence allowing proactive maintenance and safety [105]. Integrating these techniques, autonomous vehicles' operational performance adjustments to the changing road conditions will be implemented in the most efficient and safest manner possible [106];

(b) Anomaly detection: The anomalous condition of the road condition needs to be detected to recognize sudden changes so that the autonomous vehicle can react promptly on encountering a hazard [107,108] illustrated an application of One-Class SVM for the detection of anomalies in road surface data and Isolation Forests, respectively. Applications of deep learning methods, particularly autoencoders, have recently shown huge potential in the identification of subtle anomalies that traditional methods might miss [109]. Integrating these advanced anomaly detection techniques with multi-sensor data fusion strengthens an autonomous vehicle's ability to detect and adapt to road irregularities in real-time [110]. Within the proactive functioning provided by this, anomaly detection assumes a big role in ensuring safe and reliable operation for autonomous vehicles.

E. *Edge and Cloud Computing*

(a) Edge computing: This improves the efficiency of monitoring road conditions in CAVs. It also enhances responses; therefore, the number of data transmissions made with processing at the edge of the network reduces latency for better real-time decision-making. Instantaneous anomaly detection and response in smart transportation allows for the improvement of traffic safety [111]. The edge computing architecture in connected vehicles processes information locally, reducing bandwidth requirements and supporting system scalability [112]. Edge computing increases autonomous systems' resilience by providing guarantees of continuity of operation in areas with poor connectivity [113]. Finally, the integration of machine learning algorithms on edge devices offers more precision and reliability in road condition assessment [114];

(b) Cloud computing: This is a powerful system under the umbrella of cloud computing, responsible for processing and analyzing the enormous data generated by CAVs, with monitoring mechanisms provided for road conditions. Grouped data are further processed efficiently through cloud systems, which bring into play computational resources that may integrate traffic and weather data to help in the prediction of road conditions more accurately [115]. Secure aggregation and global model parameter updates on the aggregated data are conducted on cloud servers, thus ensuring that autonomous systems are updated in real-time with the most recent road condition insights [116]. In addition, cloud computing can provide secure and effective collaborative sharing of data in the Internet of Vehicles (IoV) so as to increase the collective decision-making powers for autonomous vehicles [117].

F. *Cooperative Algorithms*

(a) Cooperative perception: Cooperative perception is an awareness-sharing process between several CAVs in order to enhance monitoring of the road condition. Pooling sensor data allows for a better understanding of the environment for more clarity. For instance, based on soft actor-critic, cooperative perception models further increase the sensing range for connected vehicles to increase the sensitivity of road hazard detection [118]. Cooperative perception that integrates data from different sensors and infrastructure enhances situational awareness, which is quite useful in urban environments with complex surroundings [119]. Adaptive weighting in V2V cooperative perception further betters real-time response and lessens the impact of variability in communication on situational awareness [120]. Cooperative perception augments the robustness and reliability of autonomous vehicle networks by enabling improved awareness of vulnerable road users and safe interaction under varying traffic conditions [121];

(b) Swarm intelligence: This system employs the principles of collective behavior observed in natural systems such as ant colonies and bird flocks, ensuring optimizations in road-condition monitoring by CAVs. That is to say, autonomous vehicles can monitor and respond to road conditions collectively using decentralized, self-organizing algorithms. Other studies have found that swarm intelligence algorithms enhance the robustness of intrusion detection systems due to the ability of distributed data processing that enables the real-time detection of anomalies in autonomous vehicles [122]. The models in swarm intelligence are categorized on the basis of fault tolerance and adaptability because these are the two preeminent features that a dynamic and unpredictable environment should possess [123]. Moreover, swarm intelligence in IoT-based smart city applications supports real-time decision-making and resource allocation, especially for systems that monitor road conditions [124]. Swarm intelligence algorithms offer the possibility to converge robust solutions in real-time, while data fusion supports enhanced system reliability [125]. These results suggest the potential of swarm intelligence for revolutionizing autonomous vehicle operations toward building more robust, scalable, and adaptive monitoring systems. In conclusion, these new techniques and algorithms make it possible for connected vehicles to monitor, analyze, and react to real-time road situations. In fact, the application of such sensor technologies with advanced data processing will facilitate a real revolution in intelligent transport systems.

Table 2. Main techniques and algorithms for road condition monitoring.

Category	Techniques/Algorithm	Functionality	Application	References
Signal Processing Techniques	Kalman Filters	Filtering and noise reduction, increase real-time data reliability	Detecting road anomalies, better safety and operational efficiency	[84–86]
	Principal Component Analysis (PCA)	Feature extraction, dimension reduction	Road anomaly detection and classification	[87]
	Independent Component Analysis (ICA)	Feature extraction, meaningful pattern recognition	Road anomaly detection and classification	[87]
Machine Learning and Artificial Intelligence	Support Vector Machines (SVMs)	Classification of road anomalies and surface conditions	Detecting potholes and cracks with high precision	[89–91]
	Random Forests (RFs)	Robust classification of various road textures	Classifying various road textures accurately	[90]
	K-means Clustering	Detect and categorize road anomalies	Distinguishing between different types of road surface irregularities	[92]
	DBSCAN	Detect outliers indicative of road damage	Detecting road damage	[93]
	Autoencoders	Reconstruct road surfaces to identify deviations from the norm	Identifying deviations from the norm, enhanced anomaly detection	[93]
	Convolutional Neural Networks (CNNs)	Feature extraction from visual inputs, detect road anomalies	Detecting road anomalies such as potholes and cracks	[94–99]
Data Fusion Techniques	Multi-Sensor Data Fusion	Integrate data from various sensors for a comprehensive understanding	Improved detection of road surface anomalies	[97–99]
	Contextual Data Integration	Combine real-time sensor data with contextual information	Enhanced road condition predictions under adverse conditions	[87,100–102]
Predictive Analytics	ARIMA	Time-series analysis for predictive analytics	Predicting vehicle velocity and road gradient	[103–106]
	One-Class SVMs	Anomaly detection in road surface data	Identifying unexpected changes in road conditions	[107–110]
Edge and Cloud Computing	Edge Computing	Real-time data processing at the edge of the network	Instantaneous anomaly detection and response	[111–114]
	Cloud Computing	Efficient processing and analysis of vast amounts of data	Enhanced road condition monitoring and predictions	[115–117]
Cooperative Algorithms	Cooperative Perception	Data sharing among vehicles for enhanced road monitoring	Enhanced detection accuracy of road hazards	[118–121]
	Swarm Intelligence	Decentralized, self-organizing algorithms for collaborative monitoring	Collaborative monitoring of road conditions	[122–125]

4.2. Applications of Sensor Technologies in Road Pavement Condition Monitoring

Road Condition Monitoring (RCM) systems are typically classified into two very different types: destructive testing, which requires the removal of pavement samples to carry out specific laboratory tests; and non-destructive testing (NDT), which allows the pavement to be examined in situ without altering its configuration in any way.

Advanced sensor technologies have been integrated into next-generation vehicles, and various practical applications are in the field of road condition monitoring with the NDT approach. The areas of application are meant to ensure safety, efficiency, and the general driving experience by providing real-time data and analysis of the most common pavement distress (Figure 5). This section now gives some of the key applications of road pavement monitoring (Table 3).

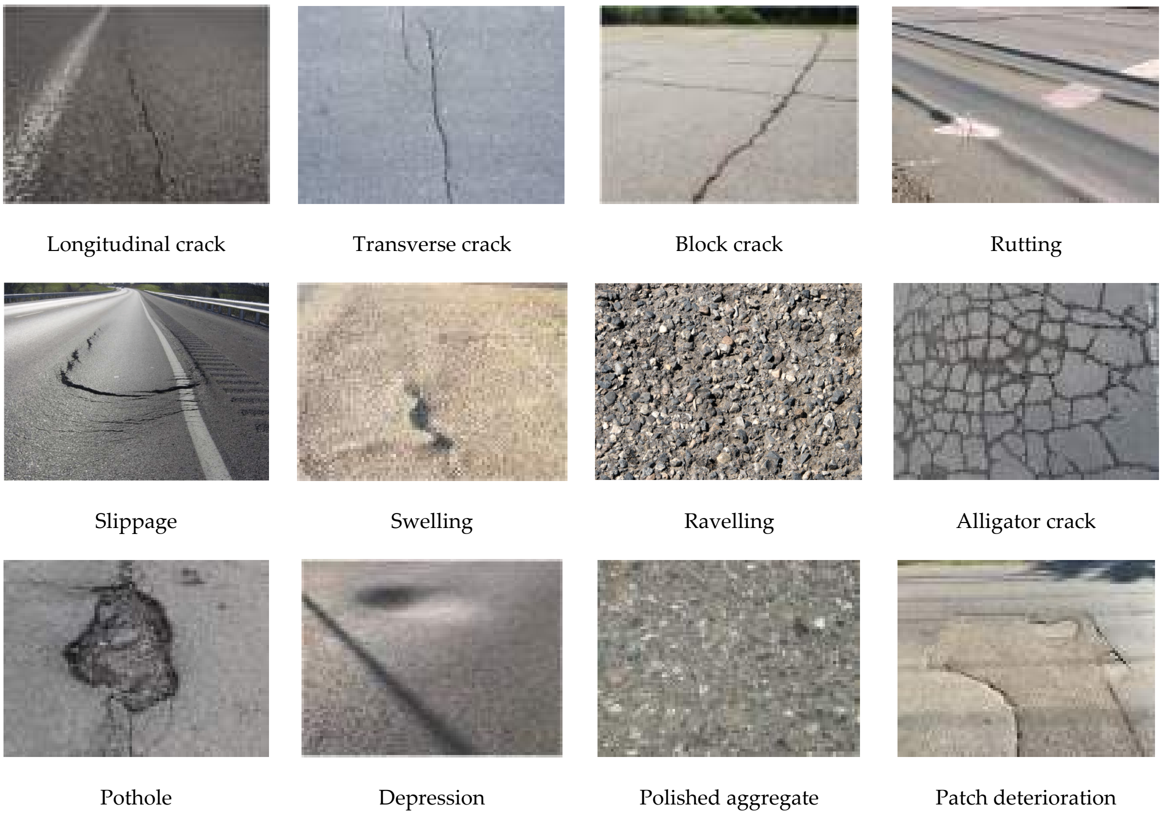

Figure 5. Examples of most common pavement defects.

A. *Pothole Detection*

Pothole detection in road condition monitoring is of great importance to CAVs; therefore, many sophisticated techniques are applied to enhance the accuracy and reliability of the process. One of the technologies largely used for its efficiency in processing and interpreting visual data is Convolutional Neural Networks, which has shown leading performance in pothole identification [126]. The fusion of LiDAR with the accelerometer data increases the detection and classification of irregularities, bringing 3D insight into consideration for higher levels of accuracy [127]. The fusion of the accelerometer and video data further improve the reliability and accuracy of the detection process, thereby reducing false-positive results [128]. In this regard, edge computing ensures real-time pothole detection to guarantee immediate actions with low latency and high operational safety [129]. These studies have collectively emphasized the effectiveness of machine learning, multi-sensor integration, and edge computing in the development of sophisticated and reliable pothole detection systems. They are crucial for furthering autonomous vehicle technology in sustaining road safety and quality.

B. *Surface Classification of pavement damages*

Surface classification is therefore of great importance to monitoring road conditions for CAVs, thus improving their safety and operational efficiency. Next-generation distributed sensors and vision-based artificial intelligence methodologies evaluate pavement distress by the measured data, their classification, and localization for improving the effectiveness of developed models in real-world applications [87]. It was shown that ensemble learning techniques give much better quality in the prediction of road surface quality from the data collected [130]. In accordance with the above, Jahromi et al. [131] presented a hybrid configuration of a camera, LiDAR, and radar sensors optimally configured for each fusion approach. Compared to benchmark models, this new architecture ensured better accuracy in road detection while keeping real-time efficiency. Furthermore, the ability to design a new deep learning concept allowed for the construction of a convolutional neural network-based road classification network, namely RCNet. This has been proven to work with great performance and accurate classification of road surfaces, even in the most complex road environments [132]. This definition is pushing forward the boundaries in our quest for fully autonomous driving systems and opens the doors to safer and more efficient transportation networks.

C. *Weather conditions*

CAVs equipped with advanced sensor technologies and deep learning algorithms are on the cutting edge for detecting icy road conditions. Using Long Short-Term Memory Networks, such devices analyze real-time data from vehicle sensors and predict pavement states: 100% for dry, 99.06% for snowy, and 98.02% for icy. This proactive detection system enables vehicles to modify driving parameters, significantly reducing accident risks and improving the overall road safety environment during such severe weather conditions [133]. Sensor technologies within connected vehicles greatly enhance the monitoring of road conditions with respect to weather changes. Such systems are also able to classify road surface conditions that have been influenced by the weather through deep convolutional neural networks, such as Inception-v3, GoogLeNet, and SqueezeNet. The optimization in performance of these networks was designed to focus on regions of interest with high precision identification for wet, icy, or snow-covered roads. This advanced classification helps make real-time decisions, improving vehicle safety and adaptability in adverse weather conditions [134]. The application of the methods provided by the deep learning of convolutional neural networks allows systems to classify road surfaces under the influence of adverse weather, such as rain, snow, and ice. Such a classification, supported by data fusion from multiple sensors, makes real-time traffic management and vehicle safety more effective by providing timely and precise information on the current state of the road and enabling better driver and autonomous system decision-making [135]. Systems using deep learning techniques such as YOLOv7 with Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) are used to enhance images before object detection is degraded by adverse weather. This hybrid approach increases detection accuracy to around 80% under challenging conditions, enabling the benefits of better decision-making and safety of autonomous vehicles [136].

D. *Pavement Crack Detection*

The sensor technology in CAVs has substantially contributed to the monitoring of road conditions and the technologies related to crack detection. Digital image processing, along with machine learning approaches, provides a real-time sensing capability for detecting cracks on road surfaces. When integrated with advanced algorithms, high-resolution cameras offer better accuracy in detection, allowing maintenance work to be performed in real-time. This guarantees road safety and prolongs the life of infrastructure [137]. In addition, deep learning and CNNs are advanced image-based methodologies capable of detecting and analyzing cracks correctly in real-time, thus saving time in detection and maintenance work due to improved accuracy and reduced human errors [138]. Using ConvNets with a learning context flux field allows the detection of minute cracks at the pixel level, even when the background is complicated. This further enhances precision in the identification of road cracks for timely repair and safety. Context flux field applies spatial context in the encoding of the relative position of crack pixels, performing better in detecting varied crack widths than traditional methods [139]. There is a recent improvement in combining INS with autonomous vehicles, which helps in the collection of vehicle altitude change data by combining acceleration sensors, gyroscopes, and GPS. The data are further processed to classify the road condition with a high level of precision in machine learning, yielding an F1 score of 99.61% [140]. In addition, based on advances in semiconductor technologies and wireless sensor networks, the cracking information, in terms of area and depth, could be automated by 3D reconstruction through stereoscopic analysis to improve efficiency and accuracy in road inspections [141].

E. *Pavement Roughness Measurement*

Sensor technologies should be employed in CAVs as they are essential for monitoring pavement roughness, particularly for crack detection. The CRSM (Crowdsourcing-based Road Surface Monitoring) system utilizes low-end accelerometers and GPS devices mounted on vehicles to record vibration patterns and location data. This information is processed through a lightweight data mining algorithm to identify anomalies in the road surface and transmit potential crack information to a central server. Applied to 100 taxis in Shenzhen, CRSM achieved a 90% success rate in identifying road potholes, proving its effectiveness in real-time road roughness measurement [142]. Onboard dynamics sensors embedded in connected vehicles capture vibration and motion data to assess road surface conditions. Advanced signal processing and machine learning techniques enable the accurate identification of road roughness and cracks without direct contact. This method supports continuous monitoring, significantly benefiting road quality and safety maintenance by providing timely data for maintenance planning and intervention [143]. In CAVs, the incorporation of sensor technologies significantly enhances road roughness measurement by using a discrete Kalman filter model with driving vibration data input. This model utilizes vehicle dynamics, filters vibration signals, and correlates them with the International Roughness Index (IRI). This cost-effective approach, requiring minimal data acquisition equipment, achieves an accuracy of approximately 88.58%, demonstrating strong engineering applicability for real-time roughness detection on asphalt and cement concrete pavements [144].

Table 3. Applications of sensor technologies in road condition monitoring.

Application	Description	Techniques/Methods	References
Pothole Detection	Utilizes CNNs, LiDAR, accelerometer data fusion, and edge computing for accurate pothole detection, enhancing road safety and quality.	CNNs, LiDAR, and accelerometer data fusion, edge computing	[126–129]
Surface Classification	Employs distributed sensors, AI methodologies, and hybrid frameworks combining camera, LiDAR, and radar for accurate surface classification.	Distributed sensors, AI methodologies, hybrid frameworks	[87,130–132]
Weather Impact	Uses LSTM networks, deep convolutional neural networks, and sensor data fusion to predict and classify road conditions under various weather impacts.	LSTM networks, deep convolutional neural networks, sensor data fusion	[133–136]
Crack Detection	Applies digital image processing, machine learning, and high-resolution cameras for real-time crack detection, enhancing road maintenance and safety.	Digital image processing, machine learning, high-resolution cameras	[137–141]
Road Roughness Measurement	Leverages accelerometers, GPS, dynamics sensors, and Kalman filter models to measure road roughness and detect cracks, improving road quality and safety.	Accelerometers, GPS, dynamics sensors, Kalman filter models	[142–144]

The more recent applications can thus exploit CAVs, or human-driven vehicles (HDVs) equipped with modern sensor technology, to greatly enhance monitoring of the condition of pavements even at the road network level (Figure 6).

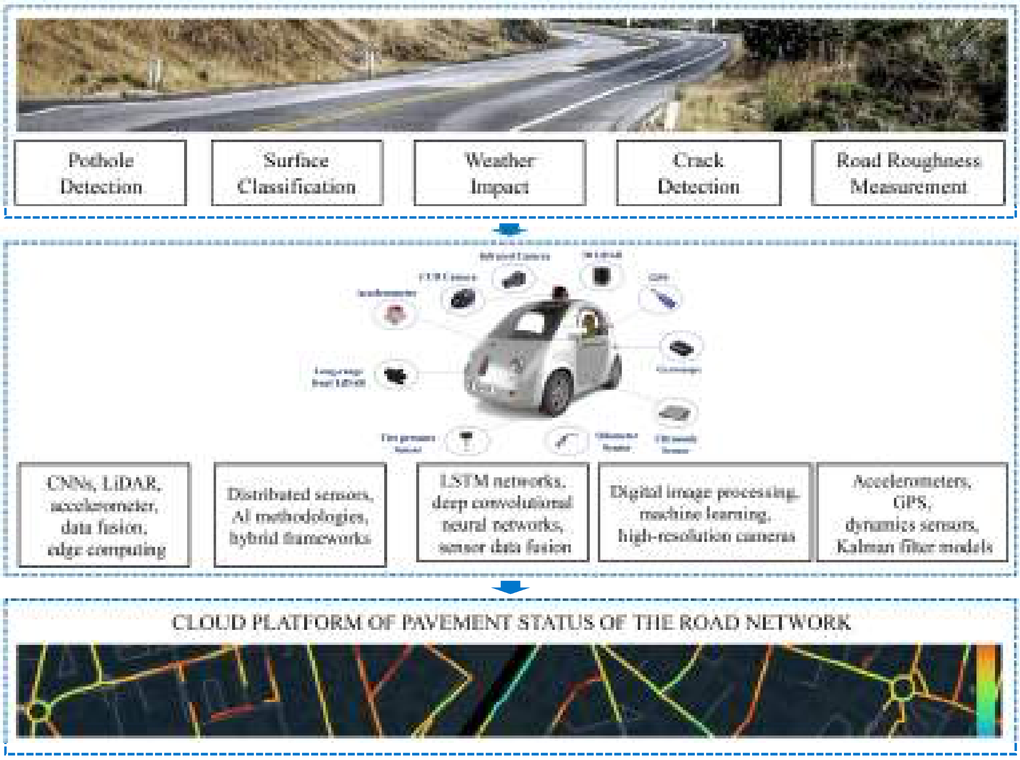

Figure 6. A framework of road network monitoring through sensor technologies implemented in vehicles.

5. Challenges and Limitations

Although the technology in sensors for road condition monitoring in CAVs has significantly progressed, it has a lot of challenges and limitations (Table 4) that require attention to reach its maximum potential. Most of these challenges are technical, economical, and regulatory in nature, meaning a broad-spectrum approach based on interdisciplinary collaboration and innovation is needed.

5.1. Technical Challenges

A. *Sensor Accuracy and Reliability*

Some technical challenges arise when it comes to how to ensure the accuracy and reliability of sensors in pavement monitoring for CAVs. As identified in the work of Rebelo et al. (2023) [145], thermal stress and sensor degradation over time were a challenge. They insisted that for the right long-term monitoring to be achieved, there must be robust sensor design and calibration [145]. The study by Masud et al. (2024) [146] outlined the selection and calibration of weigh-in-motion (WIM) systems used in pavement monitoring, addressing factors affecting sensor accuracy, such as site conditions and calibration methods. The study indicates that BP sensors exhibit the least measurement errors, followed by LC and QP sensors, while the highest errors are shown by the PC sensors [146]. However, the methods of data acquisition within the wireless sensor network that are used for pavement monitoring face challenges in relation to energy consumption, data accuracy, and network reliability. To address the challenge, Xiao et al. (2021) [147] proposed a hybrid compressive sensing (HCS) methodology that minimizes the transmission of data and balances the energy dissipated among different sensor nodes in WSNs. The system enhances the accuracy and robustness of the pavement monitoring sensors with the integrated vibration data acquisition and HCS model, thereby ensuring that data are collected in real-time and reliably [147].

B. *Data Fusion and Interpretation*

The data fusion and interpretation of pavement for monitoring within CAVs involve numerous technical challenges. The addition of such multidimensional data, which comes from different sensors that are heterogeneously formatted and of various resolutions, brings a lot of complexity with it since these sensors may include accelerometers, gyroscopes, or strain gauges. Advanced algorithms for correct merging and interpretation must be developed to secure information on pavement conditions with assurance. Other challenges are data variability, synchronization, and the assurance of system robustness under diverse environmental conditions [148]. The necessity of providing real-time capabilities—making available insights into information when they are needed— demands considerable computational resources and a truly robust network infrastructure [149]. Further improvements in the reliability of pavement condition assessments are obtained using techniques of adaptive filtering and machine learning; the effectiveness of this technique is demonstrated in extensive field testing [150].

C. *Real-time processing and latency*

The issues related to real-time processing and latency in CAVs are multidimensional, whereby the requirements needed for data transmission, processing, and time for the response are very strict. Connected vehicles require real-time processing capabilities to make spontaneous decisions regarding the safe and efficient navigation they will take. High computational demands for processing sensor data may introduce unacceptable latency in safety-critical applications. A major technical challenge, however, lies in creating complex data processing that satisfies real-time requirements. Key breakthroughs with edge computing and optimization algorithms have been directed at minimizing latency issues. This illustrates the preciseness and real-time capabilities of AI-driven solutions in detecting road defects, together with predicting road maintenance needs [151]. Research about real-time data capturing with regard to vehicle-to-vehicle communication underlines the necessity of instant data processing and its implications for safety and efficiency [152].

D. *Power Consumption and Durability*

Many advanced sensors draw huge power, which may be a limiting factor, particularly for battery-powered systems. On top of this, the sensors should be rugged and stay calibrated over time, usually in harsh environmental conditions [153]. Dutta et al. (2022) [154] revealed that a sensor system capable of functioning continuously over a long duration—during which it does not make frequent demands in terms of maintenance—would prove to be energy efficient and low in its power use; they believe that energy harvesting methodologies and low-power communication protocols are excellent ways to increase the life of a sensor further. It is very necessary to make the sensor setup robust so that the system becomes reliable and the pavement can be continuously monitored [154]. Regular maintenance or calibration of the pavement monitoring sensors could become a huge cost and logistical issue. Such demands would increase the cost of operation and make sensor networks more difficult to maintain [155]. Therefore, in effectively monitoring road conditions, the design of ruggedized and reliable sensors with low maintenance requirements is crucial. Innovations in low-power sensor design and sturdy materials are key to developing these systems.

5.2. Economic Challenges

A. *High Initial Costs*

Take, for example, high-resolution LiDAR and radar systems that feature sophisticated sensor technologies. Theoretically, good hardware implementation of such technologies is indispensable for proper and reliable autonomous vehicle operation. The high financial impact comes to a large extent from the purchase of such sophisticated sensors and their integration and calibration for proper performance under real-world conditions [156]. Such high costs may result in wide adoption not occurring, especially in low-income areas or among small transportation fleets [157]. Over time, with technology maturing and economies of scale manifesting, the costs have a great potential to reduce. However, the current expense is a big barrier [158].

B. *Return on Investment (ROI)*

Justifying investment in these advanced sensor systems involves a comprehensive understanding of their return: direct benefits to society, which lead to increased road safety and traffic management [159]; indirect benefits to society, such as reducing infrastructure maintenance costs and environmental impacts [160]. Therefore, long-term economic benefits through these investments will need to be proven by a detailed cost–benefit analysis to convince stakeholders that they are worth it [161].

C. *Cost of Maintenance and Upgrades*

Above and beyond the initial investments are the costs of maintenance and upgrading sensor systems. In fact, these sensors face physical degradation over time and may hence require maintenance or replacement on a cyclical basis [162]. With technological progression, the existing systems should, therefore, be upgraded to keep abreast with new standards and improve their performance [163]. Such upgrades remain as ongoing costs and can accumulate to very high figures in large-scale implementations.

5.3. Regulatory and Standardization Challenges

A. *Lack of Standardization*

A lack of standard protocols and interfaces among different sensor types and manufacturers may lead to poor interoperability and integration. The industry standards can make it much easier to ensure in any way possible that the sensing from different-vendor sensors can work seamlessly together [164]. Protocols developed and adopted need to be standardized and efficient in order to deploy systems for road condition monitoring on a large scale [165].

B. *Privacy and Security Concerns*

The large-scale deployment of sensors for monitoring road conditions gives rise to major issues related to privacy and security. Cyber-attacks on any sensor needing to collect and send real-time data are possible, threatening vehicle safety and user privacy [166]. Strong cybersecurity, along with privacy aspects to be taken care of through law and technology design, would be key in gaining public trust and ensuring sensitive information is not leaked [166].

C. *Regulatory Approval and Compliance*

The regulatory framework for deploying sensor technologies is immense and could, at times, in effect, become complex in covering its peripheries. Regulations are not uniform and, at times, are very complex in such a way that obtaining required approvals and compliance becomes a big challenge [6]. Harmonization of such technology among regions with simple rules on how to deploy and operate it will make the process of adoption easy and reduce regulatory burdens [167,168].

D. *Ethical and Legal Considerations*

Hansson et al. (2021) further expound on the ethical as well as legal aspects of self-driving cars, including some of the following—apportioning responsibility, blame moving from drivers to makers and maintainers, lacunae in accountability, and more. Finally, it comments on the public opinion on whether self-driving cars are safe, and the moral dilemma around them. This is supported by the fact that strict safety standards might serve as a barrier to the wide introduction of self-driving cars, while it could have saved many lives in traffic [169]. Ryan (2020) looked at the ethics in automated systems of self-driving vehicles regarding the liability of their developers for safety. He considers the reduction in traffic accidents, the programming of vehicles to make life-and-death decisions, and the societal impacts. Important ethical questions that have been raised include transparency in the algorithms, accountability, and effects on employment and privacy [170].

The real use of CAVs on existing public roads has advanced more slowly than initially expected in most countries. Nevertheless, many CAVs and the related sensors used to control these vehicles do exist already, and more will appear soon, as shown in Figure 7 [171].

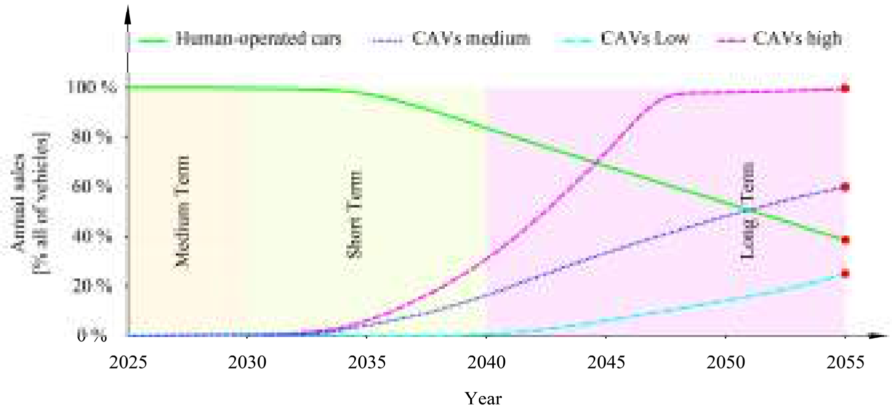

Figure 7. Qualitative evolution of annual sales of traditional vehicles and CAVs (adapted from [171]).

Table 4. Challenges and limitations in sensor technologies for road condition monitoring.

Category	Challenge	Description	References
Technical Challenges	Sensor Accuracy and Reliability	Ensuring sensor accuracy and reliability in pavement monitoring; challenges include thermal stress and sensor degradation over time.	[145–147]
	Data Fusion and Interpretation	Complex integration of diverse data from multiple sensors due to varying data formats and resolutions.	[148–150]
	Real-time Processing and Latency	Stringent requirements for real-time data transmission, processing, and response times; balancing computational demands with real-time responsiveness.	[151,152]
	Power Consumption and Durability	High power consumption of advanced sensors and the need for durability and calibration in harsh conditions.	[153–155]
Economic Challenges	High Initial Costs	Significant initial costs for deploying advanced sensor technologies, including acquisition, integration, and calibration.	[156–158]
	Return on Investment (ROI)	Comprehensive understanding of the return on investment, including improved road safety, traffic management, reduced maintenance costs, and environmental impacts.	[159–161]
	Cost of Maintenance and Upgrades	Ongoing costs of maintaining and upgrading sensor systems, including periodic maintenance, replacement, and technology upgrades.	[162,163]
Regulatory and Standardization Challenges	Lack of Standardization	Absence of standardized protocols and interfaces across different sensor types and manufacturers, hindering interoperability.	[164,165]
	Privacy and Security Concerns	Significant privacy and security concerns due to the vulnerability of real-time data to cyber-attacks.	[166,167]
	Regulatory Approval and Compliance	Complex regulatory landscape with varying regulations by region, making it difficult to obtain necessary approvals and ensure compliance.	[6,168]
	Ethical and Legal Considerations	Ethical and legal aspects of autonomous vehicles, including responsibility allocation, public opinions on safety, and programming for life-and-death decisions.	[169,170]

5.4. Physical Infrastructure Standards for the Operation of CAVs

Innovative road infrastructures, such as smart roads, are a crucial component of the operating environment of CAVs and establish where and how they can be adopted. Operating CAVs requires a specific Operational Design Domain (ODD) within the confines of the physical road [172]. Therefore, existing and new roads must match the performance and the requirements of CAVs. From this point of view, digitalized infrastructures, sensors, and smart roads are topics of great importance in the current academic community, as shown in Figure 8. This figure represents the term (keyword) co-occurrence, which is a bibliographic analysis method used to identify the main areas of interest and detect topics/subtopics that occur most frequently in the scientific literature. Figure 8 is obtained from the Scopus database and VOSviewer. The size of the nodes is proportional to the number of times a term has been used in the scientific literature. The thickness of the links between the nodes is proportional to the strength of the connection.

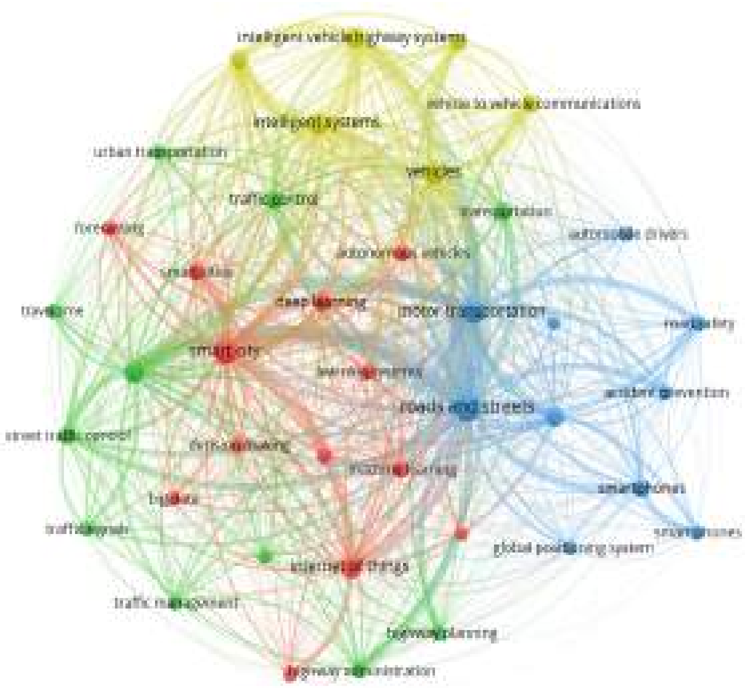

Figure 8. The term co-occurrence map: links between the keyword analysis of smart roads, sensors, and CAVs.

Research demonstrates that Smart roads essentially adopt cooperative technologies of intelligent transport systems (C-ITS) to enable communication and cooperation between CAVs. Smart roads [173,174] may employ one or more of the following traffic control systems (Figure 9): lanes for AVs and CAVs; Internet of Things (IoT) sensors for monitoring traffic flows, structures (bridges, viaducts, road safety barriers, etc.), weather, and air pollutants; ramp-metering systems; Hard-Shoulder Running (HSR) systems; variable speed limits (VSL); Green Islands (GIs); electric priority lanes; Piezoelectric devices to generate electrical energy; Smart street lights; Wi-Fi in motion; and safety barriers equipped with an accident monitoring system (AMS) [175].

In light of these considerations, policymakers should prepare for a future environment that augments the integration of CAVs, sensors, big data analysis techniques, and AI algorithms [176–179] in smart roads through investments to transform traditional roads and conventional or innovative intersections into digitalized infrastructures [150–182], with related benefits in reducing the costs of equipment for pavement analysis [183,184], many of which would no longer be necessary thanks to the use of sensors implemented in CAVs.

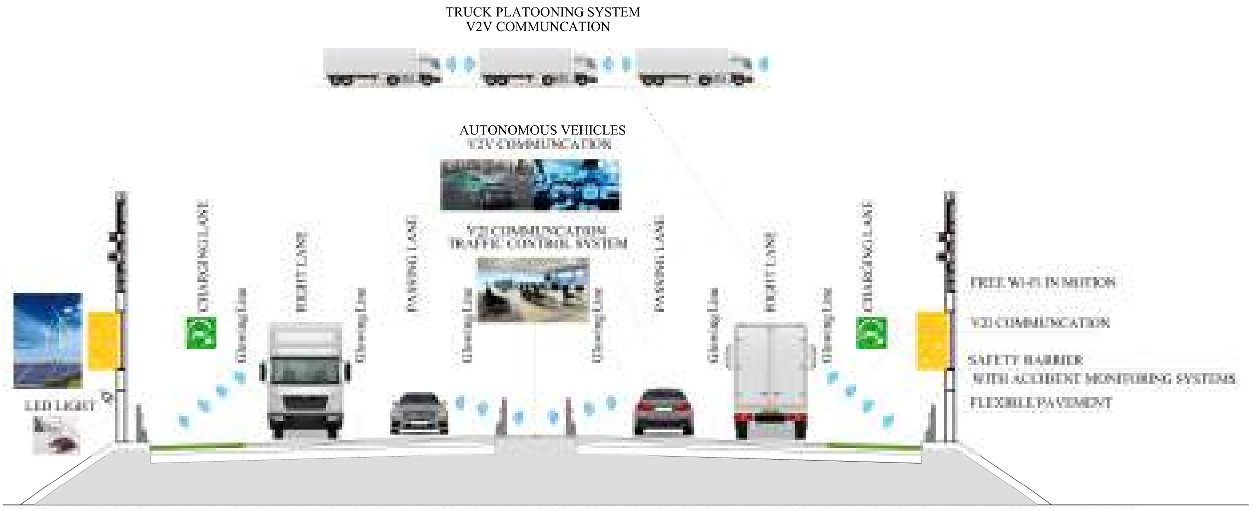

Figure 9. Smart road example.

6. Conclusions

In the fast-evolving field of intelligent transportation systems, sensor technologies in CAVs for road condition monitoring remain at the forefront with considerable recent advancement. Additionally, deep learning and machine learning techniques (e.g., CNN and LSTM) can detect and classify road anomalies such as potholes and surface cracks in a very precise and accurate way. The integration of multi-sensor data fusion from sources that include LiDAR, cameras, and accelerometers results in increased accuracy of anomaly detection and evaluation of road conditions in real time, whether it is a smart road or a traditional one. Additionally, edge computing and cloud computing are responsible for enabling such a great amount of data processing, which guarantees the monitoring of road conditions promptly and accurately, raising the operational safety and efficiency of autonomous vehicles to a high level. These developments would help policymakers and road operators and strongly support the wider goals of smart city initiatives and sustainable urban mobility.

Research Perspectives

Future research should focus on several lines to expand the current advances. The first important line is the development of low power-consuming and long-lifetime sensor systems that can work in a reliable way in many harsh environments. This requires standardizing protocols and interfaces between the many different types of sensors to pave the way for interoperability and seamless integration between vehicles and smart roads. In addition, and more importantly, advancements in cyber security measures in terms of the data collected with such sensors and the trust within the public domain are required. In conclusion, machine learning- and AI-based predictive maintenance strategies could be incorporated to optimize road condition monitoring systems by making them proactive rather than relying on reactive practices.

The future of smart vehicles and road systems is closely linked to advancements in sensor technologies, AI, and the connectivity infrastructure. The most important paths include improved vehicle-to-everything (V2X) communication that will benefit from 5G and future 6G networks, thus allowing vehicles to reliably exchange information with infrastructure in real-time. Further on, road systems based on AI will bring about predictive analysis of traffic management and road conditions; smart roads with sensors connected through the IoT will allow for it to monitor events first-hand. These updates will also include decentralized algorithms based on swarm intelligence that enhance the collective vehicle learning capability as well as green innovators such as energy efficiency designs or reduced carbon footprint.

Overcoming the depicted research and practical challenges can thus unleash the full potential of these systems for making a smarter, safer, and sustainable road transportation network.

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