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THE INTERNET OF VEHICLES (IOV) TECHNOLOGY: CHALLENGES AND SOLUTIONS

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ABSTRACT

The Internet of Things (IoT) revolution has paved the way for the emergence of Internet of Vehicles (IoV) technology, enabling seamless communication and data exchange among vehicles, infrastructure, and pedestrians. This paper delves into the IoV landscape, examining its challenges, solutions, and the role of artificial intelligence (AI) methods in addressing critical issues. The paper begins by elucidating the foundational concepts of IoV, emphasizing its potential to revolutionize transportation systems through communication protocols, Vehicle-to-Everything (V2X) technology, cybersecurity, data management, edge computing, and artificial intelligence (AI). However, realizing these benefits involves numerous challenges, including managing massive amounts of data, addressing data privacy and security concerns, mitigating network congestion, ensuring reliability, and achieving scalability. This paper comprehensively analyses IoV technology, explores the associated challenges, and presents innovative solutions enabled by artificial intelligence. By harnessing the potential of AI methods, the IoV ecosystem can evolve into a safer, more efficient, and sustainable transportation paradigm, revolutionizing how we navigate and interact with urban environments.
KEYWORDS: *The Internet of Vehicles, Intelligent Transportation Systems, Artificial Intelligence, Machine Learning, Smart Cities.*

1. INTRODUCTION:

IoV stands for "Internet of Vehicles." The idea behind it is that every vehicle should be equipped with computers, control units, and sensing platforms [1]. The Internet of Vehicles (IoV) is an emerging topic within the broader field of the Internet of Things (IoT). Through IoV, we can develop intelligent transportation systems (ITS). Devices connected within the IoV transmit a vast amount of data, which imposes costs on the IoV network [2].

Although the Vehicular Ad Hoc Network (VANET), an application of mobile ad hoc networking, is widely employed in the automobile industry, the Internet of Things (IoT) serves as the driving force behind transforming the current Internet into a fully integrated version of the future Internet. IoV is built upon this context and aims to facilitate information exchange between vehicles and all associated entities, with the goal of reducing accidents, alleviating traffic congestion, and providing additional information services. This article presents a new network architecture for the future network, designed to achieve increased data

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throughput, reduced latency, enhanced security, and improved connectedness [3].

The Internet of Vehicles (IoV) is a rapidly evolving technology that enables communication between vehicles, infrastructure, and other devices by connecting them to the internet. In order for IoV to operate efficiently, several technological issues need to be addressed. Some of the most important technical challenges that IoV should tackle include the following: communication protocols, Vehicle-to-Everything (V2X) communication, cybersecurity, data management, edge computing, and artificial intelligence (see Figure 1). In this research, the authors classified the Internet of Vehicles into three main categories: communication management, data management, and Artificial intelligence. Each subject includes issues that could be a research contribution, such as Fifth-Generation Network 5G, Vehicle-to-Everything (V2X), Edge computing (EC), Cybersecurity, and Machine Learning (ML). Furthermore, Artificial intelligence (AI) Methods have been focused on in detail.

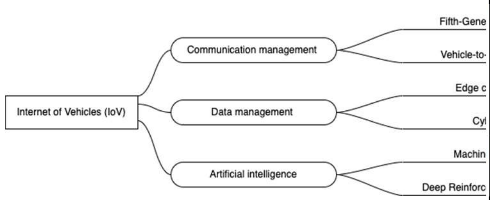

Figure 1. The Internet of Vehicles (IoV) Classification.

2. RELATED WORK

In this section, we are reviewing the recent papers has been published recently in the field of IoV.

The Internet of Vehicles (IoV) uses various wireless technologies to connect vehicles to their surroundings and share data. To ensure secure data sharing, blockchain technology can be used to mitigate IoV architecture vulnerabilities. The research examined outlines of security requirements and countermeasures, addressing severe attacks, and introducing countermeasures [4][5].

Moreover, Edge computing is essential for intelligent transportation systems, as it enables pervasive data processing and content sharing between vehicles and terrestrial edge computing infrastructures. However, it depends on connections and interactions between vehicles and technology infrastructures, which can fail in remote locations [6][7].

Combining AI and Machine Learning, IoV technology is revolutionizing the development of smart vehicles. It enables vehicles to communicate with public networks, share data, and interact with their surroundings. However, obstacles like big data connection, cloud networks, data processing, and effective vehicle-to-vehicle communication remain. AI and ML can increase the efficacy of IoV networks by addressing issues such as time, energy, rapid topology, optimization of user experience quality, and channel modelling [8][9].

Table 1. Studies related to The Internet of Vehicles (IoV) technology.

Paper	Main Topic	Publication year
[10]	VEHICLE BLACK BOX IMPLEMENTATION FOR INTERNET OF VEHICLES BASED LONG RANGE TECHNOLOGY	2023
[11]	Improved Artificial Rabbits Optimization with Ensemble Learning-Based Traffic Flow Monitoring on Intelligent Transportation System	2023
[12]	Comparative Study Analysis of ANFIS and ANFIS-GA Models on Flow of Vehicles at Road Intersections	2023
[13]	Intelligent Slime Mould Optimization with Deep Learning Enabled Traffic	2022
[14]	Multisource Data Integration and Comparative Analysis of Machine Learning Models for On-Street Parking Prediction	2022
[15]	Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms	2022
[6]	Edge-Computing-Enhanced Space–Air–Ground-Integrated Networks for Internet of Vehicles	2021
[4]	Using Blockchain Technology for the Internet of Vehicles	2021
[8]	Machine Learning Technologies for Secure	2021

	Vehicular Communication in Internet of Vehicles: Recent Advances and Applications	
[16]	A Decentralized Location Privacy-Preserving Spatial Crowdsourcing for Internet of Vehicles	2021
[9]	Machine Learning Technologies in Internet of Vehicles	2021
[5]	Blockchain application in internet of Vehicles: Challenges, contributions and current limitations	2021
[17]	A Probabilistic City Model Generation for Application in Internet of Vehicles Technology	2021
[18]	Internet of Vehicles: Key technologies, network model, solutions and challenges with future aspects	2020
[7]	Diversified technologies in Internet of Vehicles under intelligent edge computing	2020
[19]	Evolutionary V2X technologies toward the Internet of vehicles: Challenges and opportunities	2020
[20]	Research on the Development of Internet of Vehicles Technology	2019
[21]	An improved authentication scheme for Internet of Vehicles based on blockchain technology	2019

3. RESEARCH METHODOLOGY

This section defines the parameters, methodology, and paper selection criteria for the research. The section involves formulating research questions, selecting databases, defining search terms, and filtering papers. These procedures will be described in greater detail in the following section. The following section will state the research questions.

3.1 Research Questions

The main objective of this research is to clarify the technical keys, challenges, and solutions of Internet of Vehicles technology. We have two-research questions to investigate and analyse, which are:

RQ1: What are the technical solutions that should be addressed in IoV?

RQ2: What are the challenges and solutions of Internet of Vehicles technology?

3.2. Databases

Figure 2: Represents selected publishers such as IEEE, MDPI (Multidisciplinary Digital Publishing Institute) and Wiley with paper numbers per publisher and year. They are the most significant databases and have numerous publications, and researchers are always seeking to publish their work on them and provide a citation. The papers were selected according to their related to the topic of the Internet of Vehicles, and research was excluded based on the following: First: the title of the research does not cover Internet of Vehicles technologies, second: reading the abstract, and finally: reviewing and reading the research in detail.

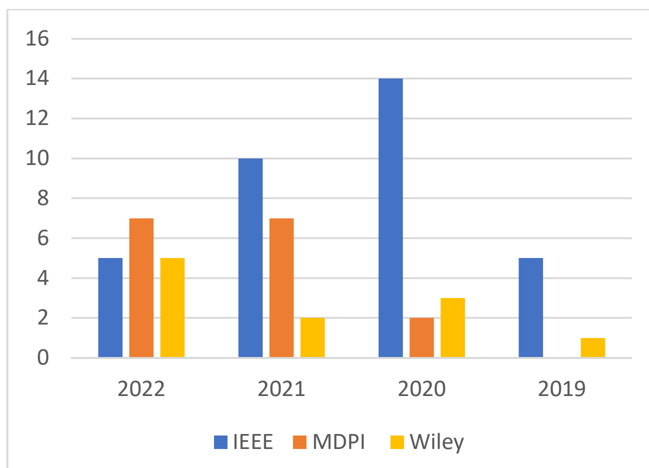

Figure 2. Papers per publisher and year

3.3 Terms and Principles

The "Terms and Principles" table summarises the concepts and definitions presented in this research. The table contains two columns, where the first column displays the name or definition while the secondary column displays the terms or principles.

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Table 2. Terms and Alternatives

No.	Terms	Alternative
1	Internet of Vehicles	(IOV)
2	Vehicle-to-Everything	(V2X)
3	Vehicle-to- Vehicle	(V2V)
4	vehicle-to-infrastructure	(V2I)
5	vehicular ad hoc network	(VANET)
6	Artificial intelligence	(AI)
7	Fifth-Generation Network	(5G)
8	Dedicated short-range communication	(DSRC)
9	intelligent transportation systems	(ITS)
10	Internet of Things	(IoT)
11	Edge-computing-enhanced Internet of Vehicles	(EC-IoV)
12	terrestrial edge computing	(TEC)
13	edge computing	(EC)
14	Software Defined Vehicular Networks	(SDVN)
15	Deep Reinforcement Learning	(DRL)
16	Markov decision process	(MDP)
17	Machine learning	(ML)
18	The adaptive neuro-fuzzy inference system	(ANFIS)
19	The adaptive neuro-fuzzy inference system optimized by genetic algorithm	(ANFIS-GA)
20	Bidirectional Gated Recurrent Unit	(BiGRU)
21	Multilayer Perceptron	(MLP)
22	Random Forest	(RF)
23	Decision Trees	(DT)
24	K-Nearest Neighbors	(KNN)
25	Gradient Boosting	(GB)
26	Adaptive Boosting	(AB)
27	service offloading	(SOL)
28	Quality of Service	(QoS)
29	Long short-term prediction	(LSTM)
30	Linear Regression	(LR)

4. THE INTERNET OF VEHICLES (IOV) TECHNOLOGY

RQ1: What are the technical solutions that should be addressed in IoV?

This section will examine the topics researchers prefer to consider when developing technological solutions for intelligent transportation systems. Including communication protocols, vehicle-to-everything (V2X), cybersecurity, data management, edge computing and artificial intelligence (AI).

Communication protocols: Communication protocols specify how devices communicate within a network. In the context of IoV, communication protocols need to be developed to ensure smooth and secure communication between vehicles, infrastructure, and other devices [22].

Vehicle-to-Everything (V2X) communication: The term V2X refers to a collection of technologies that will be developed in the future, currently represented by Dedicated Short-Range Communication (DSRC). V2X technologies enable vehicles to communicate data with other system components, laying the groundwork for intelligent transportation systems. These technologies are considered effective means of addressing issues such as traffic accidents, congestion, and pollution [23].

Cybersecurity**:** As automobiles become increasingly connected, the importance of cybersecurity issues grows more urgent. The design of the IoV system should prioritize the security and privacy of data exchanged between vehicles and other devices [24].

Data management: The Internet of Vehicles (IoV) generates vast amounts of data that need to be collected, processed, and analysed to derive insights for improving safety and traffic flow. Effective data management solutions are crucial for handling the massive data volumes generated by IoV.

Edge computing: Edge computing refers to the practice of processing data locally instead of transferring it to a central server. By leveraging edge computing, IoV systems can achieve improved responsiveness and lower latency [25].

Artificial intelligence (AI): Within the Internet of Vehicles (IoV), AI can play a crucial role in analyzing data and generating insights to optimize traffic flow and enhance safety. AI systems have the potential to enable traffic signal optimization, accident detection, and traffic pattern prediction.

4.1 Artificial intelligence methods

4.1.1 Description of Traditional AI Algorithms:

Traditional AI algorithms play a crucial role in machine learning and data analysis, offering versatile tools for classifying, regressing, and predicting data. Some examples of these algorithms include Long Short-Term Memory (LSTM), Decision Tree, Random Forest, Multilayer Perceptron, K-Nearest Neighbors, Gradient Boosting, Gated Recurrent Unit (GRU), and Gradient Boosting. Linear Regression is a straightforward technique for modelling relationships between variables, while Stochastic Gradient Descent optimizes model parameters [26]. Collectively, these traditional AI algorithms form the foundation of machine learning methodologies, providing solutions to various real-world problems with their distinctive characteristics and capabilities.

4.1.2 Applications of Artificial Intelligence in Intelligent Transportation Systems

The papers reviewed in this section aim to enhance traffic flow and management in urban areas using machine learning techniques. The first paper, by Olayode et al. [12], focuses on Comparative Study Analysis of ANFIS and ANFIS-GA Models on Flow of Vehicles at Road Intersections. The second paper, by Hamza et al. [13], proposes an intelligent slime mold optimization method combined with deep learning for smart city traffic prediction. In the third paper, Inam et al. [14] compare the effectiveness of several machine learning models for on-street parking prediction using multisource data. The fourth paper, by Xu et al. [27], presents a service offloading strategy with a deep Q-network for the Internet of Vehicles (IoV) at the network's periphery. Lastly, the fifth paper, by Navarro-Espinoza et al. [15], compares the performance of different machine learning algorithms for predicting traffic flow at various intersections using two distinct datasets.

While each document focuses on a different aspect of traffic management, they all share a common goal of enhancing road efficiency and reducing congestion. These investigations employ various machine learning techniques, including the adaptive neuro-fuzzy inference system (ANFIS), deep reinforcement learning, random forest, and gradient boosting. Most studies utilize real-world datasets, such as sensor data from automobile parking, pedestrian sensor data, and traffic flow data.

The limitations of the papers differ, with some studies recommending further research on the influence of weather conditions on traffic flow and the availability of public datasets for traffic prediction models. Additionally, the traffic scenarios used to validate the models vary across the studies. Xu et al. [27] focus on outsourcing services in the Internet of Vehicles (IoV), while Navarro-Espinoza et al. [15] predict traffic flow at various intersections.

In this study [12] aimed to compare the performance of two machine learning techniques, the adaptive neuro-fuzzy inference system (ANFIS) and the adaptive neuro-fuzzy inference system optimized by genetic algorithm (ANFIS-GA), in analyzing the flow of vehicles at road intersections. The study utilized data from Southern Africa's high traffic volume and vehicle density, with over 500,000 vehicles recorded at various times of the day. Vehicle speed, distance, and estimated time were the most important factors/variables considered in the study. Both ANFIS and ANFIS-GA demonstrated effectiveness in predicting the flow of vehicles at road intersections, with ANFIS-GA performing marginally better than ANFIS. The RTraining values were 0.8979 and 0.9709, and the RTesting values were 0.9980 and 0.9790 for ANFIS-GA and ANFIS, respectively. However, the study did not account for the influence of weather conditions on the collection of traffic datasets and the movement of vehicles. The authors suggested that future research should explore the impact of different weather conditions on traffic flow and the accumulation of traffic datasets.

Overall, the study offers valuable insights into the effectiveness of machine learning techniques in analysing traffic flow at road intersections, providing practical applications for the development of intelligent transportation systems.

In [13] the authors aims to enhance traffic prediction in smart cities through the integration of intelligent slime mold optimization and deep learning techniques. The study utilized various machine learning techniques, including in-max normalization from the scikit library, Bidirectional Gated Recurrent Unit (BiGRU), the SMO algorithm, and the SMOBGRU-TP model. The primary factor considered in the study was time duration. The dataset consisted of the preceding traffic flow data from an hour, which formed a time series of 12 data points used to forecast the traffic flow expected within the next five minutes. The data was divided into 13 sets for training and testing purposes. The proposed SMOBGRU-TP model outperformed the other models, achieving significantly lower MAPE, MSE, and RMSE values. This research demonstrates the effectiveness of the proposed machine learning techniques in enhancing traffic prediction in smart cities.

The significance of this study lies in its potential contribution to the development of intelligent transportation systems that can improve traffic flow, reduce congestion, and enhance road safety. Transportation engineering researchers and practitioners can benefit from the study's findings regarding the application of intelligent optimization and deep learning techniques to traffic prediction.

The study [14] aims to predict on-street parking availability in smart cities by integrating multisource data and conducting a comparative analysis of machine learning models. The study utilized the following models: Multilayer Perceptron (MLP), Random Forest (RF), Decision Trees (DT), K-Nearest Neighbors (KNN), Gradient Boosting (GA), Adaptive Boosting (AB), and linear SVC. Precision, recall, and F-score were the primary factors/variables considered in this study. The dataset included car parking sensor data with 35.9 million records, pedestrian sensor data with 3.09 million records, car traffic data with 60.2 K records, and meteorological data collected between January 1, 2017, and December 31, 2017. Among the models, the MLP model demonstrated the highest performance in terms of precision, recall, and F-score. The combination of parking, pedestrian, traffic, and weather data resulted in more accurate predictions of parking availability, highlighting the significance of data integration. This research can contribute to the development of intelligent parking systems, which can reduce traffic congestion, enhance the urban environment, and improve the user experience. Overall, the study provides valuable insights into the use of machine learning techniques and data integration for predicting on-street parking availability, benefiting transportation engineering researchers, practitioners, and policymakers.

The paper titled 'Service Offloading With Deep Q-Network for Digital Twinning-Empowered Internet of Vehicles in Edge Computing' by Xu et al. [27] presents a novel approach to the service offloading (SOL) problem within the context of the Internet of Vehicles (IoV) and edge computing devices (ECDs). With the objective of optimizing Quality of Service (QoS) in IoV scenarios, this study proposes an SOL method based on deep reinforcement learning (DRL). The study utilizes position, velocity, and vehicle spacing data to construct a digital twin of the traffic environment and a simulated testing platform. The performance evaluation involves dashcam footage collected from vehicle sensors and cameras. The results demonstrate that the proposed SOL method outperforms existing methods in terms of QoS performance, achieving lower packet loss ratio, lower latency, and higher throughput. This paper contributes to the existing body of knowledge by introducing the concept of digital twinning in the context of IoV and SOL, while showcasing the potential of DRL for optimizing QoS in edge computing.

The paper titled "Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms" [15] aims to predict traffic flow and enable efficient traffic control by employing various machine learning algorithms. The study discusses and applies several machines learning algorithms, including MLP-NN, Gradient Boosting, Random Forest, GRU, LSTM, Linear Regression, and Stochastic Gradient, to two datasets. The first dataset used is the Road Traffic Prediction Dataset from the Huawei Munich Research Center, while the second dataset is compiled from the PeMS dataset, which comprises more than 15,000 sensors deployed in California.

In this study, a time sequence of 12 data points is used to predict traffic flow for the next five minutes. The main factors/variables considered include traffic flow prediction for lanes 1, 2, 3, and 4, as well as metrics such as MAE, RMSE, MAPE, and R-squared, with a desired threshold of greater than 0.90. The results of traffic flow prediction show that machine learning algorithms such as GRU, LSTM, and Random Forest outperformed the other models. However, it is important to note a few limitations of the study, including the limited availability of public datasets, the focus on short-

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term prediction, and the simulation restricted to only four lanes at an intersection. Overall, this study provides valuable insights into the application of machine learning algorithms for predicting traffic flow and emphasizes the significance of efficient traffic control in smart cities. The authors of this study are Navarro-Espinoza et al. [15].

Table 3: Papers That Using AI Algorithm Technique.

Authors/Date	Research Objective	ML techniques Used
Olayode et al 2023	Comparative Study Analysis of ANFIS and ANFIS-GA Models on Flow of Vehicles at Road Intersections	The adaptive neuro-fuzzy inference system (ANFIS), The adaptive neuro-fuzzy inference system optimized by genetic algorithm (ANFIS-GA)
Hamza et al 2022	Intelligent Slime Mould Optimization with Deep Learning Enabled Traffic Prediction in Smart Cities	Bidirectional Gated Recurrent Unit (BiGRU), SMO algorithm, SMOBGRU-TP model
Inam et al 2022	Multisource Data Integration and Comparative Analysis of Machine Learning Models for On-Street Parking Prediction	Multilayer Perceptron (MLP), Random Fores, (RF), Decision Tree, (DT), K-Neares, Neighbors (KNN), Gradient Boosting (GA), Adaptive Boosting (AB), linear SVC
Xu et al 2020	Service Offloading With Deep Q-Network for Digital Twinning-Empowered Internet of Vehicles in Edge Computing	Service offloading (SOL), Deep reinforcement learning
Navarro-Espinoza et al 2022	Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms	MLP-NN, Gradient Boosting, Random Forest, GRU, LSTM, Linear Regression, Stochastic

		Gradient

Table 4 shows some of the papers' results after applying the model they proposed, which was concluded using the evaluation measures (explained in the next section).

Table 4: Shows The Papers Results Using The Evaluation Measures.

Paper	ML	MAPE (%)	RMSE	R^2
[12]	ANFIS ANFIS-GA	-	-	0.9790 0.9980
[13]	AI-TFP SMOBGRU-TP	21.364 18.560	17.31 16.011	-
[15]	MLP-NN GB RF GRU LSTM LR SG	21.1593 21.9493 21.8392 22.8492 22.3244 24.3238 29.0075	15.42 15.41 15.54 15.61 15.67 15.85 18.37	0.9304 0.9305 0.9296 0.9278 0.9267 0.9263 0.9003

The papers conclude by demonstrating how machine learning techniques have the potential to enhance urban traffic management. These studies provide valuable insights into the performance of different algorithms and models, emphasizing the importance of using specific and diverse datasets in the development of effective traffic prediction models. By addressing the challenges highlighted in these studies and validating the models across various traffic scenarios, researchers can further improve the field of traffic management.

4.1.3 Evaluation Measures

Evaluation metrics are crucial for assessing the efficacy of machine learning models and algorithms. Accuracy, Precision, Recall, and F-Measure are four commonly used evaluation metrics. These metrics provide insights into various aspects of model performance, enabling a comprehensive understanding of its strengths and limitations.

Collectively, these evaluation measures provide a nuanced assessment of a model's prediction accuracy and are extensively used to guide model selection and optimization in numerous domains.

Accuracy: A classifier's accuracy is determined by its ability to effectively predict the effect of a predicted feature on new data.

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$$1.\ \text{Accuracy} = \frac{TP+TN}{TP+TN+FP+F}$$

Where:
- (TP) True positive cases predicted as yes.
- (TN) True negative cases that are predicted as no.
- (FP) False positive cases that are predicted yes and it is yes.
- (FN) False negative cases predicted as no but it is yes.

Precision: Precision is determined by dividing the number of accurately classified positive predictions by the total number of correctly or inaccurately classified positive predictions.

$$2.\ \text{Precision} = \frac{TP}{TP+FP}$$

Recall: The recall of a prediction is calculated by dividing the proportion of correctly classified positive predictions by the total number of positive predictions.

$$3.\ \text{Recall} = \frac{TP}{TP+}$$

F-Measure: The F-measure is a single measure that conveys both recall and precision, calculated using the next Equation:

$$4.\ \text{F} - \text{Measure} = \frac{2*\ \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

In model evaluation, the root-mean-squared error (RMSE) and mean absolute error (MAE) are two standard metrics [28].

$$1.\ RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$2.\ MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

5 CHALLENGES AND SOLUTIONS

RQ2: What are the challenges and solutions of Internet of Vehicles technology?

This section will review the challenges in the Internet of Vehicles and some proposed solutions to improve transportation systems in urban cities, including managing massive amounts of data, addressing data privacy and security concerns, mitigating network congestion, ensuring reliability, and achieving scalability.

Big Data: One of the major concerns in the Internet of Vehicles (IoV) is the storage of large volumes of data generated by numerous connected vehicles, including driverless automobiles, which are projected to process 1 GB of data per second. To address this challenge, effective management of big data through techniques such as big data analytics and mobile cloud computing is crucial [29].

Mobility: Maintaining continuous connectivity and ensuring real-time broadcasting and receiving of resources becomes challenging in the context of rapidly moving cars and dynamically changing network topologies [29].

The mobility of nodes in Internet of Vehicles (IoV) poses challenges in accurately analysing the number of participating nodes in the network. Even if vehicles have sufficient energy to utilize computing and communication resources when they connect with surrounding objects, maintaining a stable connection becomes difficult due to the diverse and rapid mobility of vehicles, leading to additional issues. For instance, the limited transaction times caused by vehicle mobility constraints make it challenging to deliver critical vehicle data [5].

Reliability: It is important to acknowledge that automobiles, sensors, and network hardware can experience failures. The system should be designed to handle inaccurate data and poor communications, including potential security threats like denial-of-service attacks. In general, prioritizing vehicle safety is more crucial than focusing on entertainment [29].

To support mission-critical applications, transportation systems, including first responder communication and transportation systems, require services with low communication latency and high reliability. The Internet of Vehicles (IoV) possesses various characteristics, such as limited wireless connection bandwidth, rapid vehicle mobility, rapid data transfer, and heavy computing load. These characteristics must be managed within a predetermined time frame to avoid potentially dangerous situations [5].

Security and Privacy: The Internet of Vehicles (IoV) ecosystem requires robust security and privacy solutions to mitigate the risks associated with false and malicious information exchanges between vehicles. Such exchanges can lead to accidents, data security vulnerabilities, and reliability issues. These risks can be categorized into physical, communication, and application domains. The various components of the IoV are susceptible to criminal activity and unauthorized access at a physical level, while communication-level challenges involve ensuring secure and prompt transactions and interactions. Additionally, issues with cloud services at the application level may result in data loss or insufficient storage capacities [5].

Given that IoV involves the integration of numerous technologies, services, and standards, data security becomes paramount. It is susceptible to cyberattacks and intrusions, which can lead to data breaches and physical harm [29]. In table 4, a summery of these papers are provided.

Table 4. Challenges and solutions of IoV technology.

Technological Aspects	**Challenges**	**Solutions**
Big Data	A significant number of connected vehicles generates a substantial amount of data for processing and storage.	Mobile cloud computing will manage the massive amounts of data.
Mobility	It is difficult to maintain nodes connected and to send and receive in real-time when vehicles are moving fast	Network stability for non-stop connections must be provided.
Reliability	The system must cope with both inaccurate data and faulty communications.	Priority must be given to vehicle safety
Security and Privacy	IoV could be the target of cyberattacks and incursions, resulting in data breaches and physical harm	A data security and privacy system must be effective.

This research has some limitations, such as the number of publishers that have been used, including IEEE, MDPI, and Wiley. Moreover, recent papers written five years ago have been cited in this research. Also, this research focused on AI, but communication and data management need to be explained in future work.

6 CONCLUSION

AI-powered Internet of Vehicles (IoV) technology revolutionizes traffic efficiency and promotes environmental sustainability by integrating AI methods and addressing the complexities of vehicles, transforming transportation systems. Within the IoV landscape, solutions driven by AI techniques address key concerns such as data privacy and security, network congestion, and interoperability. Through the use of deep learning algorithms, predictive analytics, adaptive routing, and reinforcement learning, AI empowers optimized traffic signal control and route planning. The transformative potential of AI-driven IoV systems calls for continuous research and innovation, aiming for a safer, more efficient, and environmentally conscious future. The synergy between IoV and AI creates a wiser and more connected world, propelling the development of a smart transportation ecosystem. This research has provided answers to two essential questions regarding the Internet of Vehicles: the technical solutions that should be addressed and the challenges that will be encountered, including dealing with a huge amount of data, nodes connected to send and receive in real-time, reliability, and cyberattacks and incursions. Thereby assisting researchers in examining the field.

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