future internet

MDPI

Review

Intelligence-Based Strategies with Vehicle-to-Everything Network: A Review

Navdeep Bohra [1], Ashish Kumari [1], Vikash Kumar Mishra [2], Pramod Kumar Soni [3,*] and Vipin Balyan [4,*]

[1] Department of CSE/IT, Maharaja Surajmal Institute of Technology, New Delhi 110058, India; navdeepbohra@gmail.com (N.B.); ashishkumari@msit.in (A.K.)
[2] Department of Electrical Engineering, University of Cape Town, Rondebosch 7700, South Africa; mail2dr.vikash@gmail.com
[3] Department of Computer Applications, Manipal University Jaipur, Jaipur 302007, India
[4] Department of Electrical, Electronics, and Computer Engineering, Cape Peninsula University of Technology, Cape Town 8000, South Africa
* Correspondence: pramod.soni@jaipur.manipal.edu (P.K.S.); balyanv@cput.ac.za (V.B.)

Abstract: Advancements in intelligent vehicular networks and computing systems have created new possibilities for innovative approaches that enhance traffic safety, comfort, and transportation performance. Machine Learning (ML) has become widely employed for boosting conventional data-driven methodologies in various scientific study domains. The integration of a Vehicle-to-Everything (V2X) system with ML enables the acquisition of knowledge from multiple places, enhances the operator's awareness, and predicts future crashes to prevent them. The information serves multiple functions, such as determining the most efficient route, increasing the driver's knowledge, forecasting movement strategy to avoid risky circumstances, and eventually improving user convenience, security, and overall highway experiences. This article thoroughly examines Artificial Intelligence (AI) and ML methods that are now investigated through different study endeavors in vehicular ad hoc networks (VANETs). Furthermore, it examines the benefits and drawbacks accompanying such intelligent methods in the context of the VANETs system and simulation tools. Ultimately, this study pinpoints prospective domains for vehicular network development that can utilize the capabilities of AI and ML.

Keywords: intelligent vehicular networks; Artificial Intelligence; machine learning; vehicular ad hoc networks; Vehicle-to-Everything

check for updates

Academic Editor: Stefano Rinaldi

Received: 18 December 2024
Revised: 26 January 2025
Accepted: 5 February 2025
Published: 10 February 2025

Citation: Bohra, N.; Kumari, A.; Mishra, V.K.; Soni, P.K.; Balyan, V. Intelligence-Based Strategies with Vehicle-to-Everything Network: A Review. *Future Internet* **2025**, *17*, 79. https://doi.org/10.3390/fi17020079

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Vehicle ad hoc networks are a subset of mobile ad hoc networks (MANETs) that enable wireless communication among mobile vehicles [1]. At present, automobiles are outfitted with on-board units (OBUs) that comprise a variety of sensors and transmitting devices [2–4] Vehicles participate in communication with a variety of vehicles, including roadside units (RSUs), through the utilization of OBUs. VANETs potentially have a substantial influence on the development of contemporary Intelligent Transportation System (ITS) infrastructure [3], as they establish connections with Wide Area Networks (WANs) via RSUs to facilitate authorized entry and information retrieval for internet-based applications [5]. Recent advancements in AI methodologies have presented novel prospects for ITS. This development has facilitated the implementation of autonomous driving, which operates by emulating the actions of human drivers while minimizing the impact of human error. Numerous applications, from self-driving vehicles to smart vehicles or the Internet

of Vehicles, are now growing, beginning with active and passive highway security, forecasting congestion [6], and road safety and extending to driver assistance [7] and traffic optimization [8]. As shown in Figure 1, the fundamental basis of the vehicular network involves carrying data through the utilization of the following types: Vehicle-to-Everything (V2X), vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V), Vehicle-to-Network (V2N), Vehicle-to-Pedestrian (V2P), and vehicle-to-roadside units (V2R). Within VANETs, the relay of signals across vehicular networks can be facilitated using V2V communications.



Figure 1. Types of VANET communications.

This network mode enables vehicles to transmit data on highway situations, including mishaps and congestion. An RSU, made up of a stationary infrastructure device linked to the web and capable of facilitating communication with moving vehicles and other RSUs, receives data transmissions from nearby RSUs. RSUs guarantee data transmission's dependability and are beneficial in numerous critical incidents [9,10]. In VANETs [11], a V2V connection is deemed obligatory while RSUs are not near vehicles. The V2N communication model relies on 3G/4G/5G cellular networks utilized for vehicular surveillance because they offer extensive reachability and facilitate fast data sharing [12]. The V2P connection model involves sharing information among vehicles and pedestrians. An in-vehicle communications model involves interaction within vehicles to identify and evaluate automobiles to reduce mishaps caused by driver sleepiness or vehicle problems [13]. The dynamicity of traffic flows, physical structures, and transmission within vehicular communications (V2X) is quite intense. Furthermore, the increasing prevalence of mobile

applications, including inside vehicle information technology systems, is putting wireless connectivity under unprecedented load. Consequently, Mobile Network Operators (MNOs) will be obligated to amass a tremendous volume of diverse information to oversee network efficiency and deliver improved amenities. Considering the present network methodologies, ensuring the functionality while adhering to various Service Level Agreements (SLAs) will progressively escalate in complexity. This issue can be resolved by implementing additional intelligence in the network [7]. Self-organizing Networks (SONs), for instance, are independent and flexible structures that enable vehicular networks to determine what steps are required to sustain efficiency stability and enhance Quality of Service (QoS) levels. SON technologies are classified as self-configurable, optimized, and healing entities. This technology works when a problem is already generated. AI and ML may be explored as prospective remedies for integrating intellect into SONs. Such solutions would anticipate impending network problems and be capable of handling the intricacies suitably. A vehicular network primarily focuses on efficiency in three key fields: energy, vehicle safety, and traffic. Traffic flow details are the significant application of V2X. These vehicle details can be utilized by vehicular networks to effectively carry out operations including the resolution of congested roads, the optimization of Plug-in Electric Vehicle (PEV) battery usage, the reduction in petroleum intake, and the enhancement of Global Positioning System (GPS)-based services. Various resources, including closed-circuit television (CCTV) recording devices, crowd-sourced databases, and vehicles, are capable of providing traffic flow statistics [14].

Developing traffic flow forecasting systems that are exceptionally precise while utilizing traditional traffic flow analysis techniques presents a significant obstacle. Not only that, but study and testing are constrained to just a small subset of available traffic data. Researchers have a limited amount of freely accessible statistics to work with when developing and testing methods to forecast traffic flows. ML has been extensively used to construct prediction models in various domains like visualization, robotics, healthcare, and Natural Language Processing (NLP). ML techniques employ Supervised and Unsupervised Learning to better manage sparse and dense nodes of vehicles. ML in VANETs includes handling data congestion, driverless transportation facilities, clustering, stability, storing information, and geographical location applications [15–17]. Nevertheless, there exists significant potential for expansion within the domain of ML emergence techniques to address the issues with vehicle networks.

1.1. Research Contributions

This article presents the following work:

1. A summary of previous work in this area of ML and V2X connectivity.
2. An extensive examination of the various AI and ML approaches with vehicular networks to focus on multiple VANET issues and necessities.
3. The enumeration of unresolved investigation obstacles that must be surmounted to actualize the capabilities offered by this intimidating technology.
4. A detailed examination of network simulation techniques, encompassing their respective merits and drawbacks.
5. The identification of areas of future study that demand more analysis to integrate ML with VANET fully.

1.2. Paper Organization

The rest of this manuscript is organized in the following manner: Section 2 provides a comprehensive outline of the V2X background and an overview of ML techniques in VANETs. Section 3 presents ML and swarm technique foundation and techniques in detail.

The simulation tools for VANET that are accessible for the development and implementation of AI and ML algorithms are in Section 4. This article describes AI and ML applications for the vehicular network in Section 5. Section 6 outlines the scope and problems of the future of ML and vehicular network platforms to maximize the integration's potential benefits and provide open issues in this field. Section 7 concludes this article. The complete structure of this article is depicted in Figure 2.

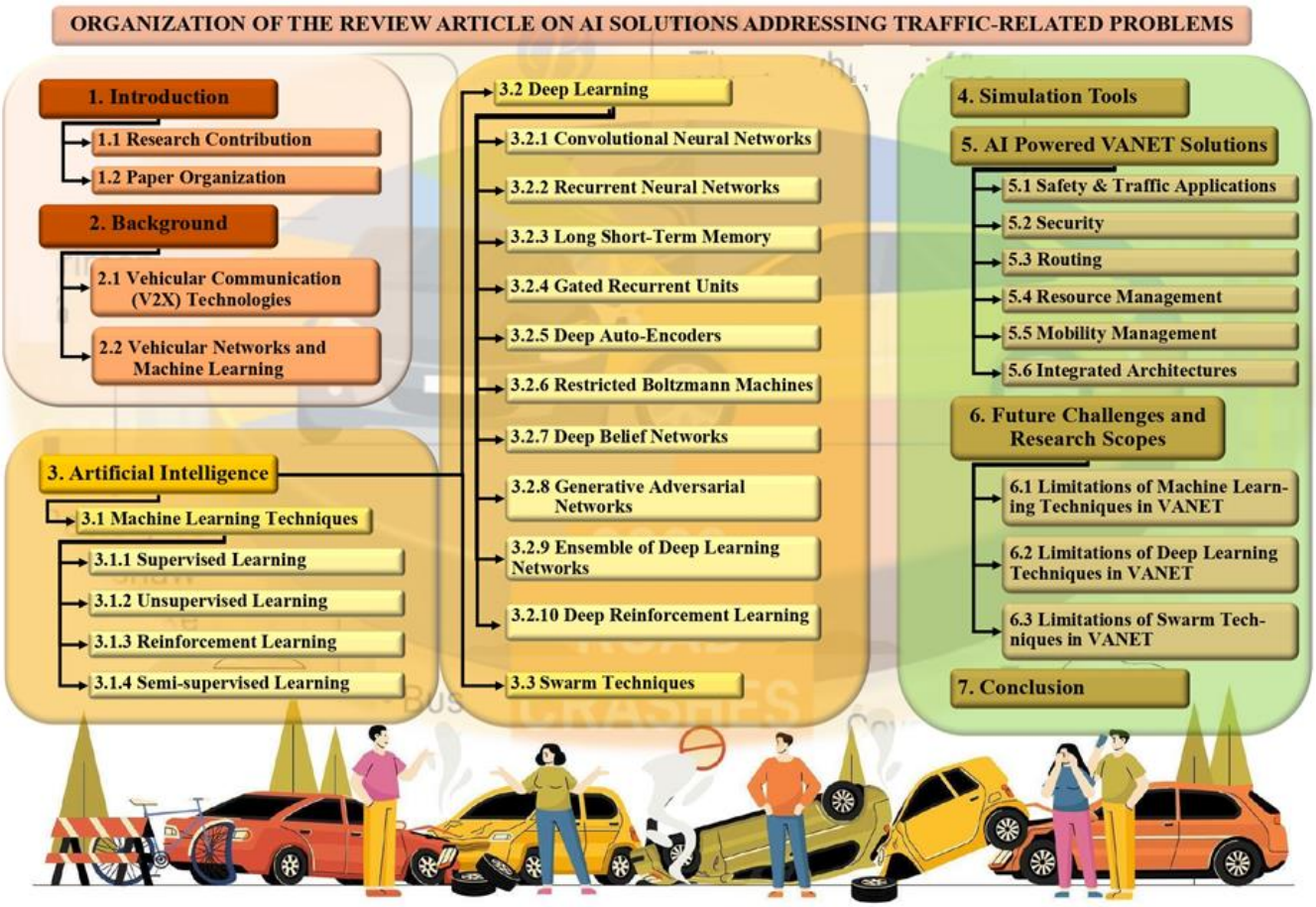


Figure 2. The structure of the complete section.

2. Background

VANETs have been a highly researched field for more than ten years. Advancements in computer science have contributed to a rapid increase in the application of AI approaches across multiple sectors such as medicine, transportation, production, engineering, and medical services, among many others. The primary objective of vehicle networks is to augment the security and efficiency of transportation by enabling the seamless interchange of data across auto vehicles and RSUs. A fundamental classification of AI involves two main methodologies: ML and Deep Learning (DL), discussed below in detail. Currently, these techniques are employed in various real-life situations because of their remarkable ability to solve issues. In the past few years, there has been substantial advancement in both fundamental ML and DL. This part presents a succinct description of VANET communication technology and the significant use of ML methods with vehicular ad hoc networks. Additionally, this article analyzes and explores certain locations within VANETs where such technologies can be efficiently employed.

2.1. V2X Technologies

A proliferation of interconnected and fully autonomous vehicles on the roads is causing significant innovations in the transportation and automotive sectors, resulting in improved reliability and safety. There are two powerful technologies of VANETs for V2X, i.e., Dedicated Short-range Communication (DSRC) and Long-Term Evolution (LTE)-based technology [18]. The very initial design of the V2X was constructed by utilizing dedicated DSRC and the IEEE 802.11p network protocol [3,19]. The DSRC protocol is a "full duplex wireless network facility, enabling highly rapid data transfer rates crucial to communications-based security programs", as the U.S. Department of Transportation defines it. In 1999, the Federal Communications Commission designated 75 MHz of spectrum within the 5.9 GHz band (5.850–5.925 GHz) to implement vehicle security and transportation services. It is an open-source wireless communication protocol with certain resemblances to WiFi, designed to facilitate ITS applications (V2V and V2I), fast speeds, and secured and short-range communication among vehicles and infrastructure. Enhancing the whole transportation experience, reducing traffic jams, and improving traffic safety are the primary objectives of DSRC. V2V communication via VANET is free of infrastructure, which is crucial to guarantee security among underdeveloped and faraway places, particularly on misty roads. Common Awareness Messages (CAMs) and Basic Safety Messages (BSMs) can be transmitted by automobiles in DSRC at less than 100 milliseconds. DSRC, a minor alteration of the IEEE 802.11 protocol, facilitates the deployment of VANETs. The Medium Access Control (MAC) protocol of DSRC is based on Carrier-Sense Multiple Access/Collision Avoidance (CSMA/CA), which can result in unrestricted delays and stability [20], despite the fact that VANET nodes can connect to the internet rapidly. The invention of the DSRC protocol from the year 1999 to 2020 is presented in Figure 3. After the year 2020, it will be upgraded with IEEE 802.11bd to enhance the performance at a higher speed. In contrast, the LTE specification is widely implemented as a fundamental aspect of 5G technology and is presently undergoing further development as 4G broadband wireless technology [19].

LTE is characterized by its exceptional dependability, expanded bandwidth, and the necessity for pre-deployment alterations in the V2X system [3,21]. Vehicular-to-everything communication, which facilitates collaboration between cars, will enhance situational consciousness and perception of roadside infrastructures, pedestrians, and other road elements in this particular environment. Cellular-vehicle-to-everything (C-V2X) [12] is becoming increasingly popular for connecting and automating vehicles in the coming years, particularly for sidelink LTE-V2X Mode 4. It uses a PC5 interface in the 5.9 GHz band to transmit and receive messages for vehicular ad hoc networks. Two powerful technologies of cellular-V2X communication that come under the umbrella that is used for V2X are LTE-V2X and 5G-V2X.

The physical connectivity of LTE, called sidelink, has been released by the most recent 3rd Generation Partnership Project (3 GPP) standards for LTE V2X. This differs from the conventional uplink and downlink network traffic of LTE. The LTE V2X is capable of operating in two distinct modes via sidelink: first, LTE-V-Cell mode, for long-range (wide-area) communications that employ the mobile network for direct radio transmission between the C (UE) and the Base Station, called eNodeB (eNB); second, LTE-V-Direct mode, which employs sidelink as the physical link [22] by employing independent Time Division Multiple Access (TDMA), as Medium Access Control (MAC), in which the duration is partitioned into segments. Before entering the connection, the communication devices must connect to the link by arbitrarily selecting an unoccupied slot after initially listening to the carrier to collect packet information. Nevertheless, total avoidance of collisions is unattainable due to concurrent channel selection. Traditional cellular networks can facilitate unicast,

broadcast, and multicast connections. Nevertheless, the substantial messaging latency associated with these setups renders them unsuitable for transmitting CAM messages. To cater to the requirements of transportation systems, the 3GPP started the standardization process for the LTE-V specification in Release 14 [3,22,23]. This standardization is intended to facilitate V2P, vehicle-to-V2I, and vehicle-to-V2V services, collectively called V2X services. The standard has devised a novel channel model utilizing the PC5 interfacing to accommodate automotive networking demands. Additionally, the standard supports the traditional unique user interface for various transportation applications [3]. Release 12 of the LTE standard, used for public safety, saw the development of the sidelink, which enables D2D connectivity and is a component of the PC5 link. V2X communication capabilities are undergoing enhancements in LTE Release 15 and are scheduled to receive additional improvements in Release 16 [23].

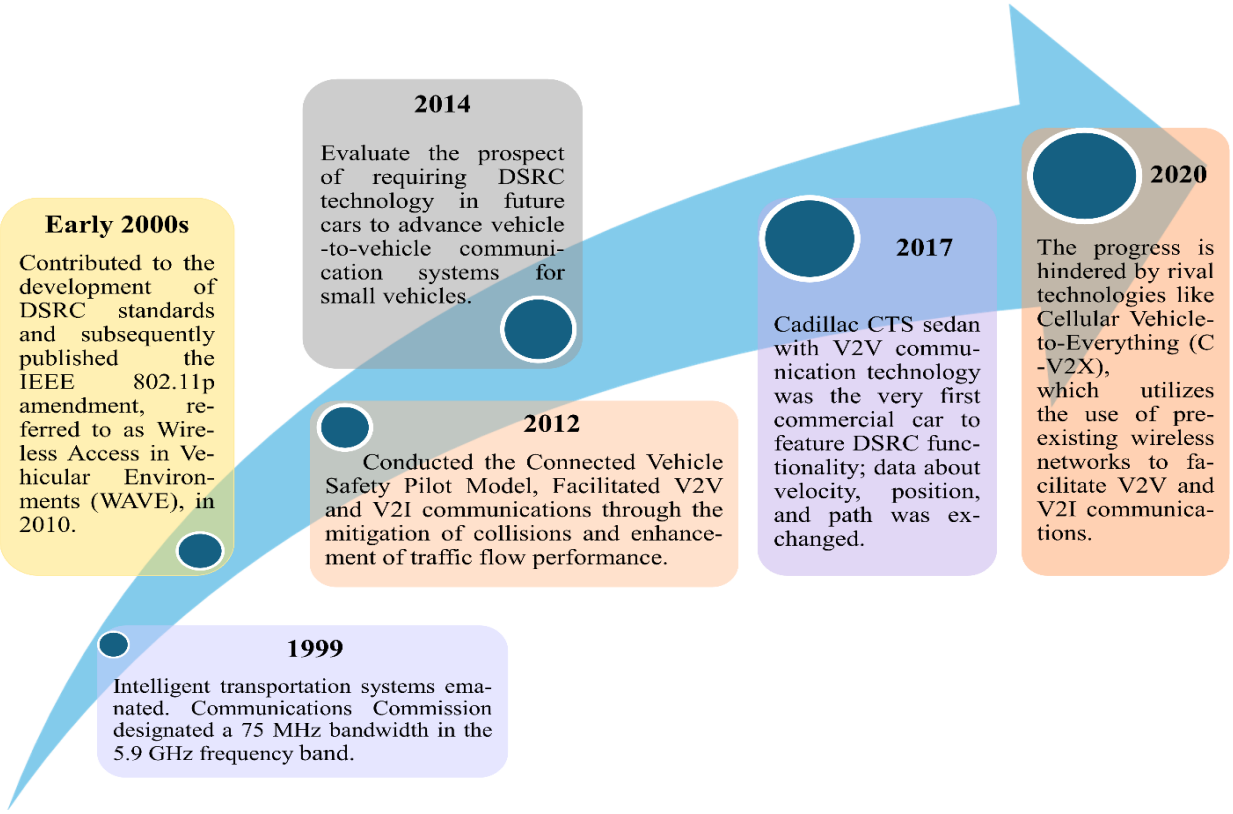


Figure 3. DSRC feature invention.

A revolutionary foundation for transforming mobility and automotive systems is created when 5G technology is coupled with Internet of Vehicles (IoV) technologies. Enabling VANET communication is made ideal by this synergy, which enables low-latency, ultra-reliable, and smooth connection with extraordinarily high bandwidth. 5G improves the security, efficiency of traffic, and user experience in IoV networks by allowing fast data transmission and real-time connectivity across infrastructure, cloud systems, and automobiles. Combining this with fog/edge computing helps to address one of the major problems with the Internet of Things (IoT): processing data in real time from different locations. Fog/edge computing, in contrast to conventional, centralized cloud systems, moves processing capacity towards the source of data, which in this case is automobiles and roadside infrastructure. Applications such as autonomous driving, collision avoidance, and adaptive traffic management rely on this closeness to drastically decrease latency. This also reduces bandwidth usage by performing analysis close to the source, reducing the quantity of unprocessed information transferred to main servers. The Internet of Vehicles

relies on 5G and fog/edge technologies to support efficient, intelligent, and responsive vehicle networks that can adapt to the ever-changing needs of contemporary transportation networks [11].

Cellular networks, including LTE and 5G, offer multiple benefits compared to DSRC. These include increased bandwidth, wider service area, and better data transmission rates. Nevertheless, cellular networks exhibit certain limitations in comparison to DSRC technology. The following are provided below:

- V2X communication in DSRC is a decentralized communication that operates directly between peers without requiring any involvement from a network administrator. However, the cellular network demands assistance from a network provider.
- In a cellular network, information is transmitted via the uplink and downlink lines to reach where it is supposed to go. However, in DSRC, information may be immediately conveyed to the endpoints without any intermediate steps.
- The cellular system requires network access to function. However, DSRC can transmit information anywhere by simply broadcasting it over airspace.
- DSRC is significantly more cost-effective than the cellular network.
- DSRC is solely for V2X communication, in contrast to cellular networks which share bandwidth among competitors' users.

2.2. Vehicular Networks and ML

The accelerated advancement of computational innovations in the past decade has enabled the extensive implementation of AI techniques in a variety of sectors, such as production, medical fields, technological development, and healthcare, among others. The primary goal of VANET protocols is to enhance the performance and safety of vehicular networks through the facilitation of sharing information among vehicles, pedestrians, and RSUs. To facilitate services including congestion control, roadway security, and entertainment, VANETs collect information from a variety of locations. VANETs routinely collect knowledge from a variety of sources, including V2V and V2I interaction (velocity, position, guidance, signage, signals, and toll booths), sensors (vehicle inside sensor systems, road sensors, and roadside structures (traffic conditions, mishaps, weather current information), all contributing to this pool of information [3,4]. Data are gathered in VANETs through various methodologies. An example of a networking protocol that is tailored for VANETs facilitates communication between V2V and V2I nodes. Additionally, data transmission among automobiles and infrastructure is accomplished via cellular networks, particularly for distant or non-real interaction. The storage and processing of VANET data on cloud-based systems facilitate central administration and analysis in real time. Nonetheless, there are obstacles to data capture in VANETs, including issues of dependability, confidentiality and safety, connections to networks, adaptability, integration, and so on. An amalgamation of innovative technology, reliable communication, trustworthy and effective systems for managing data, and group collaboration—including that of infrastructure service providers, government agencies, and transportation manufacturers—is required to tackle these issues. Notwithstanding these obstacles, the prospective advantages of VANETs in enhancing motorist accessibility, highway effectiveness, and crash prevention render it an auspicious domain for scientific investigation and advancement. It is necessary to equip vehicles with sensors and navigational equipment like GPS, media gadgets, and wireless components to participate in VANET. To prevent mishaps or abrupt stops, automobiles can utilize sensors and media gadgets to perceive their surroundings and identify items like other moving nodes, obstructions, and people. Alternatively, wireless transmission units offer several kinds [24] of network linkages which may be classified relative to the communicating units as shown in Figure 4.

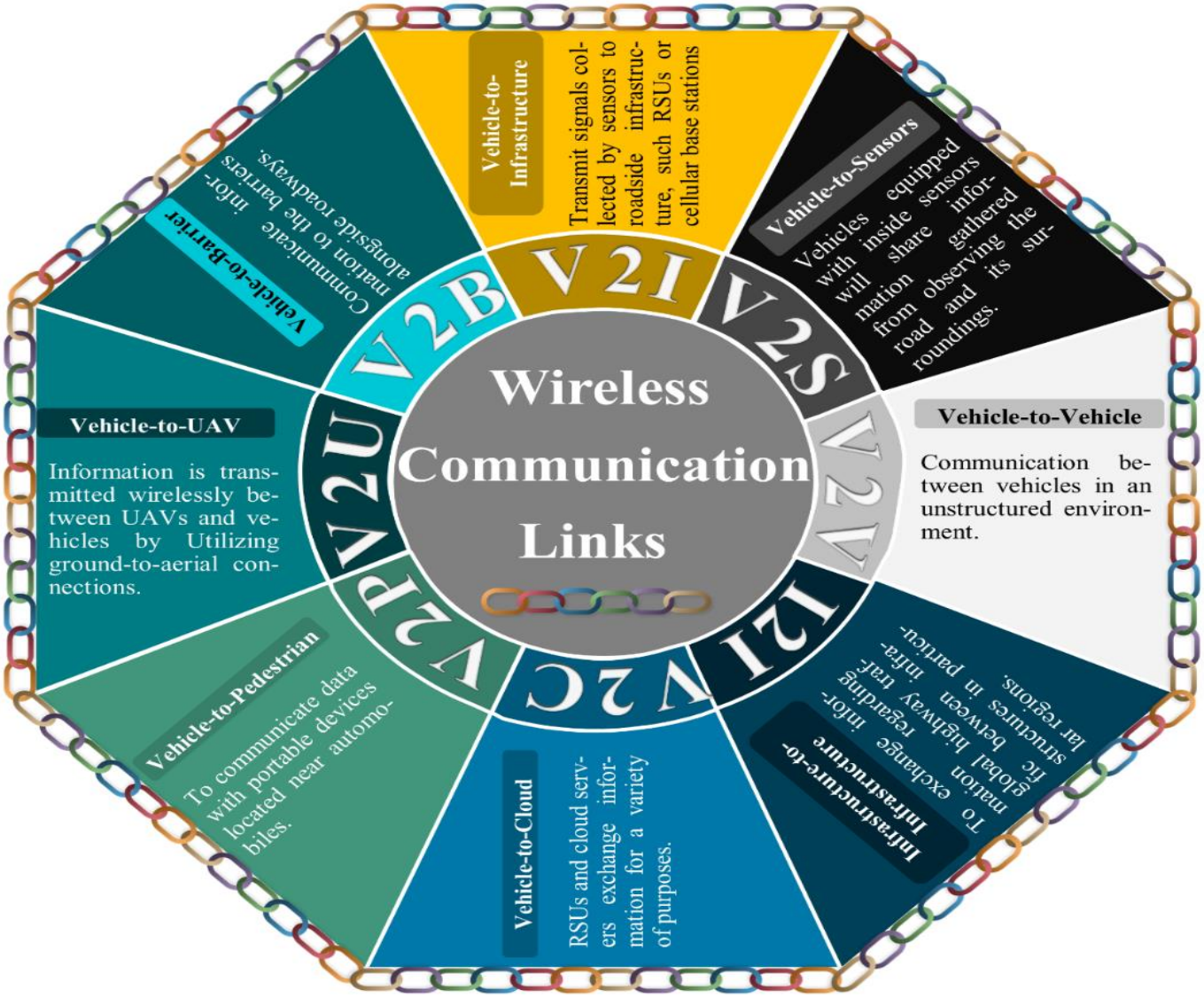


Figure 4. Wireless communication links.

The data gathered in VANETs play a substantial role in enabling streamlined routing, improving driver consciousness, and predicting variations in movement [25]. In addition to safety-relevant data such as incident warnings and highway risks, immediate-time traffic situations, accident details, and highway congestion notifications facilitate dynamic route planning and optimization. Historical and real-time mobility data aid in the prediction of upcoming requirements and trends in transportation. To accomplish these objectives, particular methodologies and models are implemented. The dynamic routing methods choose routes in response to circumstances such as traffic jams and mishap warnings. Users are promptly notified through context-aware messaging systems, while appropriate data are superimposed over the vehicle's range of sight via heads-up displays (HUDs) and augmented reality. By analyzing previous information, time series evaluation and ML prediction algorithms discover movements and predict future patterns. V2V and V2I networks facilitate the sharing of information instantaneously, which is utilized for optimum traffic movement and navigation. In 1959, ML was initially proposed by Arthur Samuel. ML is a subfield of AI that enables computers to acquire new computational abilities and improve their performance over time without the need for human interaction [26]. Although the literature contains numerous definitions of ML, two leading experts in the field, "Arthur Samuel and Tom Mitchell", offered succinct explanations of the terminology. Samuel de-

fines ML as the process by which machines acquire the ability to execute predetermined operations despite the need for direct programming. ML, according to Tom Mitchell, is the development of computer applications that enhance independently with practice. The notion that "a computer program learns from experience about certain types of tasks and performance measurement" was utilized to substantiate his definition. "The performance measured concerning the task is enhanced with increasing experience [27]". In doing so, ML helps systems make accurate data-based predictions. ML models are capable of pattern recognition and decision-making. ML models acquire knowledge from their past analysis states and independently collect new information, make decisions, and provide outputs. Pattern recognition, text recognition, speech recognition, vision, and robotics [28] are just a few of the numerous areas it helps tackle. ML is a huge area with many different classification schemes. A broad categorization classifies ML methods into four distinct groups based on the type of learning executed: Supervised, Unsupervised, Semi-supervised, and Reinforcement Learning (with an emphasis on deep Reinforcement Learning).

Machine-based algorithms consist of entities that interpret their surroundings and modify their behavior via learning to accomplish a particular goal. ML is a fundamental subsection of AI concerned with the investigation of how entities' perceptions can be enhanced through knowledge or learning. To identify latent trends within datasets, ML algorithms approximate an intended expression that generates predictions on information that has not been observed before. The capacity of ML algorithms to extrapolate their insights from observed test data to unobserved instances is a critical component [29]. DL has emerged as a result of developments in Graphics Processing Units (GPUs) and the enhanced accessibility of information in recent decades. DL is a critical subfield of ML that exhibits superior accuracy compared to traditional ML methods when confronted with substantial data volumes. DL is built upon Artificial Neural Networks (ANNs), a well-known ML technique that draws inspiration from the learning process occurring in our bodies. In light of the above, machine-based systems may facilitate the implementation of sophisticated vehicular network cases, especially emergency braking, collaboration, and crossroad situations. These types of cases necessitate the training of a learning agent with vast quantities of knowledge by conditions obtained by the fundamental use case. Subsequently, the agents will execute actions while adjusting themselves to accommodate dynamic highway and communication situations. It is critical to maintain constant interaction among automobiles, networks, and pedestrians, irrespective of the route and network congestion, to facilitate these transport use cases. For V2X communications to continue without interruption, the underlying control and management processes have to be operational and enable the transmission and reception of consciousness alerts. This article showcases the various AI and ML applications made possible by emerging communication networks in several fields, as seen in Table 1.

Peer-reviewed articles have led to significant advancements in various fields and have made valuable contributions to the existing body of literature. Reference [30] provides a focused analysis of ML applications in the context of IoT, specifically highlighting their utilization in a particular area. The major focus of reference [31] is to examine the uses of Convolutional Neural Networks (CNNs) in a particular area, along with its associated smaller issues. The researchers of the investigation offer a comprehensive analysis of CNNs' computational views in the given field. A paper provides a succinct summary of AI techniques in many elements of urban planning [32]. ML, Cognitive radio, VANET, and Cognitive radio-VANET architectures, procedures, challenges, and unanswered questions are addressed in article [33]. ML techniques' CR-VANET applications are examined. A survey of AI applications in a certain topic and its associated sub-issues is discussed in reference [34]. A study presents a survey of ML methods and their uses and difficulties in

forthcoming mobile-based networks [35]. A text discusses an assessment of ML applications in a specific area. It also explores the combination of ML and IoT systems to create smart devices in this field [36]. The investigation conducted in [37] aims to investigate many problems regarding the utilization of freely available information in a particular field within the context of ML techniques. In [38], an examination is conducted to analyze the uses of ML in the area of wireless sensor networks. The research presented in [39] focuses on analyzing various kinds of learning techniques. The article [40] introduces an analysis of research on ML usage for a certain topic, together with the key results of the evaluated publications. The research presents a complete assessment of ML algorithms and their uses in IoT devices within an area. The analysis provides detailed descriptions of the research. The investigation in [41] identifies related issues within a particular field related to network systems. Its next section examines relevant articles, presenting ML and implementation details, such as efficiency and database details. In addition, the study also examines ML methods specific to the area.

Table 1. Past work on VANETs using ML.

Ref.	Year	Technique	Used with	Objective	Future Scope
[30]	2019	ML	IOT	Efficient vehicular networks and related applications discussed	ML for Smart Lighting Systems and Smart Parking applications
[31]	2020	CNN	ITS	Efficacy and examined the utilization of CNN in ITS; detailed classifications of the problems	CNN for object detection and analysis
[32]	2020	AI, ML, DRL	Cybersecurity, smart grids (SGs), 5G, B5G	Best services of 5G and beyond 5G (B5G) communications, and smart healthcare system	ML and DRL for seamless power supply between different communications
[33]	2020	ML	Cognitive radio (CR) VANET	Covering various designs, processes, difficulties, and unresolved inquiries.	Interference and shadowing problem using ML
[34]	2020	AI	Distributed smart grid	Distributed intelligent grids; integration of renewable energy resources	Self-healing grid; plug-and-play technique
[35]	2021	ML	6G wireless communication	Addressed B5G/6G network-enabled platforms' wireless communication	Model Agnostic Meta-Learning (MAML); GANs
[36]	2021	ML	IOT	Utilizing ML and IoTs by smart vehicular networks.	Data security
[37]	2021	ML	IOT	Context of smart living, smart governance, smart economy, and intelligent transport	DL techniques to solve smart city issues
[38]	2021	ML	Wireless Sensor Networks (WSNs)—IoT	ML used with WSN-IoT to address smart city problems	Heart stroke rehabilitation system using ML
[39]	2021	ML	Power system	ML techniques described with smart grid power system	Force framework security and control
[40]	2021	ML	IoT integrated power system	Potential uses in solving issues plaguing contemporary power systems	-
[41]	2021	ML	VANET security	Address various safety issues inside vehicle communications and security threats	Blockchain-integrated ML solutions

Table 1. *Cont.*

Ref.	Year	Technique	Used with	Objective	Future Scope
[42]	2022	ML	V2X	Classifies routing using learning-based or non-learning-based; V2X routing protocols	ML integration with Blockchain, 5G, 6G, OceanNet, VANET architecture
[43]	2022	AI	VANET	AI and ML methods investigation in the field of VANETs	AI for task scheduling, prediction algorithms, and resource allocation for QoS
[44]	2022	AI, ML	VANET Security	AI to address vehicular security	AI-based security techniques
[23]	2023	AI, ML	V2X	AI/ML with V2X networks	Black box and energy-efficient-based AI/ML algorithms
[27]	2023	AI, ML	Future mobile communication	ML with wireless communication technologies, smart energy, and intelligent healthcare	Blockchain with DL
[45]	2024	ML	Smart Transportation Networks	Address cognitive radio and ML affect intelligent vehicular networks' spectrum sensing; security concerns affect VANET and CR improved VANET	Designing and evaluating a cognitive radio enhanced (CRE) VANET framework
[46]	2024	ML	Opportunistic networks	ML-technique-driven methodologies with opportunistic networks	ML-based best forwarder node, congestion detection, energy consumption

3. Artificial Intelligence

AI refers to the study and development of ML algorithms that possess the ability to recognize things, make informed choices, and exhibit human-like behavior. Intellect is described as the ability to gather and use knowledge and abilities. Consequently, a person with intelligence has to gain knowledge efficiently by utilizing many approaches, such as making findings, gaining insights from past encounters, evaluating data, understanding language, and engaging in conversations using individuals. The system can make decisions, set and achieve goals, analyze and understand language and pictures, and more, using the knowledge it has acquired. A machine is deemed intellectual if it possesses the ability to comprehend written information, engage in cognitive processes, and successfully resolve complex issues. AI is a vast area which includes Machine Learning, DL, and swarm techniques.

3.1. ML Techniques

Conventional AI/ML techniques fall into four classes based on how learning is executed, i.e., Supervised, Unsupervised, Reinforcement, and Semi-supervised Learning [23]. Semi-supervised Learning is the mixture of Supervised and Unsupervised Learning. Different types of ML algorithms, including online learning and transfer learning for data classification. ML consists primarily of two critical phases: training and assessment. During the training phase, an algorithm is developed using testing actual data. Subsequently, predictions are generated during the testing phase using the trained model. Table 2 represents the categories of ML and DL techniques.

3.1.1. Supervised Learning

Supervised Learning involves input and output data, referred to as features and labels in the information set, accordingly, during the learning process of models. The final

goal is to predominantly determine by the label, specifically whether there is an issue of classification (label represents a discrete variable) or a regression issue (label represents a continuous variable). A goal function establishes an association between the identifiers and the features. The model learns a rough estimation of its goal function by modifying its variables until it achieves the optimum result throughout the training process. A collection of pre-established hyperparameters, including the learning rate and sample size, govern the learning procedure. These parameters are user-defined and finalized by the trainee before the commencement of the training phase. Essentially, this refers to an optimization issue in which the result is assessed using a distinct assessment dataset, which did not take part in the training session to prevent overfitting. SL can be categorized into two main fields, i.e., Classification and Regression Algorithms.

Table 2. Categorization of ML [3,26,33,42] and DL techniques [26,33].

Types of ML and DL	Prediction Goal	Process	Techniques	Real-Life Uses
Supervised Learning	Qualitative, Quantitative	Classification and Regression	Decision Tree (DT), Naive Bayes, Support Vector Machine (SVM), K-nearest neighbors (KNN), Random Forest, Linear Classification, Ensemble Learning, linear and logistic regression.	Flat Price, Medical imaging
Unsupervised Learning	-	Clustering, Association, and Dimensionality	K-means, hierarchical clustering, Gaussian Mixture Model (GMM), Markov Chain (MC), Hidden Markov Model (HMM), Principal Component Analysis (PCA), and AR	Market Basket Analysis
Reinforcement Learning	Qualitative, Quantitative	Classification, Control, and Regression	Q-learning, Double Q-learning, Markov Decision Process, and Deep Q-learning	Optimization, Speech, Text, and Image Recognition
DL	Qualitative, Quantitative	Classification, Control, and Regression	CNNs, Recurrent Neural Networks (RNNs), Long Short-Term Memory, Gated Recurrent Units (GRUs), Deep Neural Networks (DNNs), Deep Auto Encoders, Deep Belief Networks, Deep Reinforcement Learning, GANs, deep auto-encoder, and Restricted Boltzmann Machines	Identify Objects

A. Classification Algorithms

1. DTs' prevalence as a classification and prediction tool [47] is attributable mainly to their accessibility. A DT comprises a root element, which receives incoming data, and leaf nodes that represent the categorization of queries and answers, respectively. Every reaction functions as a necessary condition to enable subsequent investigation within the next layer [48]. This classification tool is characterized by its simplicity and ease of use, making it highly advantageous in the context of automotive networks, for detecting misbehavior, managing roadway signals, and making routing decisions [49].
2. SVM, also known as Large Margin Separators, is a category of learning methods that were initially designed for predicting a binary qualitative variable or discriminating [50]. These predictions were subsequently extrapolated to a quantitative variable. Discrimination of a binary variable is achieved through the identification of the optimal margin hyperplane, which properly divides or classifies records while remaining as far from every measurement as possible. This method is robust due to its capacity to process data containing a substan-

tial quantity of attributes but a limited number of input cases. Therefore, it might be a viable method for identifying malicious actors and mitigating and identifying security breaches within the VANET environment. Additionally, it facilitates cluster optimization and spectrum allocation improvement [51].

3. The Naive Bayes (NB) technique used for Supervised Learning for a classification approach categorizes a collection of samples by the rules that the technique generates [52]. Given the assumption that the categories within the training dataset can be distinguished, the supervised character of the program is reflected in the Naive Bayesian classifier. Naive Bayesian demonstrates suitability for addressing various VANET challenges, including driver behavior prediction, broadcast storm avoidance, and transgression awareness [53]. This is owing to its robustness against irrelevant attributes, straightforward deployment, and minimal training needs.
4. The KNN algorithm is a method of Supervised Learning. It is capable of performing both classification and regression. To generate a forecast, the KNN algorithm employs the complete dataset. In the context of predicting an observation that is not present in the information set, the technique conducts a search for the K instances within the collection that exhibit the highest degree of proximity to the desired insight [54]. Using the corresponding images of these K neighbors, the algorithm then computes the value of the predicted output of the observation. KNN is an effective architecture for location identification, privacy preservation, and stability [55].
5. Random Forest generates results that can be generalized and are easy to train and comprehend. A Random Forest is constructed from a collection of distinct DTs [56]. This problem is viewed in a fragmented fashion by all trees due to the implementation of a twofold random selection process. Random Forest is resistant to overfitting and does not require feature selection. It requires a minimal number of input values. Due to these merits, it is an effective method for resolving congestion forecast issues, executing handovers (particularly for the transmission of multimedia records), and organizing bandwidth allotment [57,58].
6. Linear Classification: The application of linear classification in ML and data mining is beneficial. Although linear classifiers are inadequate for handling inseparable data, they can be satisfactory for processing data in a high-dimensional space. On document data, for instance, linear classifiers have been demonstrated to perform comparably to nonlinear classifiers. One significant benefit of linear classification is the marked improvement in the efficiency of training and testing procedures. Linear classification is thus potentially advantageous for some large-scale applications. Linear classifiers encompass well-known techniques including logistic regression (LR), SVMs, and others [43,59].
7. Ensemble Learning (EL) or Multiple-Classifier Supervised Learning is the application of meta-algorithms that compose an amalgamation of numerous ML techniques. These techniques are implemented to diminish uncertainty and bias, while concurrently enhancing the precision of predictions [60]. It is an approach to diminish overfitting and can decrease variation by acting as a proficient converter, converting diverse data into a standardized representation, as opposed to merely performing classification tasks. Employing EL as an ML technique efficiently improves the reliability of vehicle location, assists in transfer decision-making, and detects misconduct [61].

B. Regression Algorithms

1. Linear Regression: The validity of regression models is contingent upon the association between independent and dependent variables, as well as the quantity of independent variables incorporated. The linear regression technique is an extremely effective and basic ML approach that provides a means of predicting the value of an unknown or dependent variable using a given dataset of independent factors [62]. This method operates under the equivalent presumptions of a linear relationship, constant variance, and independent features. L2 regularization, an alternative method, can effectively manage independent features in a database that are highly correlated. This is achieved by imposing restrictions on the coefficients and penalizing the total squares of the weights [63]. Linear regression can be applied to trend prognosis, result prediction, and causal investigation. The coefficients are obtained by the simplest estimation method via mean-square error. Incorporating resilience toward anomalies into the LASSO, Ridge, or ElasticNet regressor architectures was implemented [26].
2. The logistic regression algorithm is implemented to address classification issues [64]. It operates on the principle of probability and employs methods for predictive analysis. In it, a growing cost function is utilized. This cost capacity more closely resembles the logistic function, or sigmoid function, than a linear function. Logistic regression restricts the cost function to the interval encompassing zero and one. Logistic and linear regressions are both encompassed within the Generalized Linear Model (GLM), a comprehensive framework that integrates numerous other statistical models [26]. Table 3 describes the Supervised Learning methods' primary advantages, issues, and uses in the VANET domain.

3.1.2. Unsupervised Learning

Unsupervised Learning investigates unlabeled datasets for patterns. In contrast to SL, the absence of pre-labeled input–output pairs eliminates human oversight. Unsupervised methods utilize characteristics such as orthogonality, correlations, statistical separability, and so forth to self-infer relationships between variables. Clustering or classification techniques, on key evaluation elements, are, although not entirely, the most prevalent unsupervised methods. We are starting to rely on unsupervised DNN-based techniques, including Generative Adversarial Networks (GANs) [26]. Unsupervised Learning performs the main tasks based on three categories, clustering, association, and dimensionality, as discussed below.

1. The K-means algorithm is an unsupervised non-hierarchical clustering algorithm that is part of a specifically exclusive method. By employing this approach, the input knowledge can be classified between k different clusters [65]. As a result, data that are identical will be located in the corresponding cluster. Furthermore, it is imperative to underscore how the knowledge being analyzed is limited to a single cluster at any moment, indicating limited merging [66]. Therefore, a single fact cannot simultaneously belong to two different clusters. The application of this methodology offers benefits when dealing with confidential information as it can function despite the need for annotated data. As a result, it ensures the reliability of VANET clustering effectively, bolsters the protection of hash operations when confidential data are transmitted, and is well suited to be utilized in congestion discovery [67]. Fuzzy K-means is an overlapping technique of Unsupervised Learning with the soft-hand approach.

2. Hierarchical clustering [HC] begins by considering the data points as distinct clusters. Subsequently, they are progressively merged or divided according to their similarity or dissimilarity. This approach involves the division of terminals into groups based on both geographical and social affinity; hierarchical clustering algorithms facilitate the efficient transmission of messages inside every group [61,68]. This process generates a dendrogram, which resembles a tree. Two distinct types of agglomerative hierarchical clustering were examined in this research. It has two main parts, agglomerative and divisive. Agglomerative is a bottom-up approach that includes four distance methods for measuring similarity, i.e., word linkage, average linkage, complete linkage, and single linkage. All these techniques can be calculated with the help of Euclidean distance. Divisive clustering is a top-down approach [61].
3. GMM clustering is a probabilistic clustering method used to solve density estimation or soft clustering problems and operates under the assumption that observations are produced by combining a finite set of Gaussian variables. Introducing covariance into the issue, this probabilistic model synthesizes the uncertainty of cluster assignments modeled with k-means [69]. The objective of this approach is to represent a given dataset as a combination of numerous Gaussian probability distributions. More precisely, when provided with a dataset consisting of N observations denoted as $\times 1$, $\times 2$, …, $\times N$, the GMM clustering function aims at determining the variables of K Gaussian distributions that may accurately represent the data [31]. By manipulating the quantity of Gaussian mixtures, GMM is capable of fitting arbitrary distributions, enabling it to accurately characterize the impact degradation process [70].
4. MC is a stochastic model that specifies a possible order of instances so that the present situation alone determines the probability of each event. The possible states of an MC with finite states are discrete, or countable. The MC operates in a memoryless manner, as the transition from one state to the next is exclusively determined by the current state and the associated transition probabilities [71]. The data-driven model made use of the MC Monte Carlo and Gaussian Process methodologies [27].
5. HMM: Baum and his co-authors introduced the HMM concept in a succession of papers published during the 1960s and 1970s. Subsequently, HMMs have been effectively implemented in numerous domains, including speech recognition by machines [72].
6. PCA is an essential DL method utilized in feature extraction, that aims to derive additional and better-defined characteristics from pre-existing ones. An input dataset containing "n" predictor variables is provided. To acquire a covariance matrix, which is a n $\times$ n matrix, the predictors are centered with their respective means. After decomposing this matrix, Eigenvalues and Eigenvectors are obtained. Therefore, PCA provides a procedure that employs a covariance matrix to quantify the relationship between variables, Eigenvectors to determine the directions of data dispersion, and Eigenvalues to emphasize the relative worth among those areas [73]. This AI approach might be utilized in a VANET situation for both caching optimization and security risk prediction [74]. The ability of the system to decrease the magnitude of the data collected simplifies the optimization methods.
7. Association Rule (AR) is categorized as a component of ML and data extraction as a result of its application in processing data. AR is highly effective at identifying recurring trends in data to forecast future behaviors. The successful implementation of AR in the finding of vehicular incidents, along with the production of routes and maps tracked by vehicles, is made possible through the finding of fundamental correlations [61,75]. Table 4 describes the Unsupervised Learning methods' primary advantages, issues, and uses in the VANET domain.

Table 3. Supervised Learning: primary advantages, uses, and issues in the VANET domain.

ML Types	Advantages	Uses Areas in VANET	Issues
DT	Transparent and user-friendly	Efficient routing option; optimizing traffic signal control; identifying aberrant actions shown by malevolent vehicles	Large space required;
SVM	Manages dataset; high dimensionality and limited amount of data elements	Avoiding and identifying assaults, i.e., vehicle misbehavior, intrusion, Sybil, Greyhole, Blackhole, and Wormhole; detecting unauthorized vehicles; cluster optimization; enhancing decision-making process for spectral distribution	Optimal kernel; opaque and unintuitive
Naive Bayes (NV)	System resilient, disregarding or removing unimportant attributes; straightforward to build and minimal training needs	Enhances prediction accuracy; mitigates the occurrence of broadcast storms and reduce accidents; identification of malfunctioning vehicle	Zero-frequency problem; Estimations can be inaccurate in certain instances
KNN	Optimal categorization using voting	Identify and track instances of effective inside attacks accurately; safeguard privacy by protecting essential details; enhance and preserve cluster stability; identify vehicular mishaps and provide alerts for sites	High time complexity; Euclidean distance measure may not be universally applicable to all datasets; requirement for substantial quantity data
Random Forest	Addresses the issue of overfitting; avoids the necessity for feature selection with low input data	Forecasting vehicular traffic jams; enhancing handover assistance for the distribution of multimedia content across vehicles; allocating control channels; high accuracy on large datasets	Analyzing outcomes without adequate hyperparameter tuning; possible misclassification of instances belonging to the minority class
Linear Classification	Classification algorithm; outcome by evaluating the numerical sum of the features	Significant increase in the effectiveness of the testing and training processes; capacity to be helpful for certain large-scale applications, including logistic regression, SVM, etc.	Insufficient for managing indivisible data
EL	Resistant to overfitting and reduces variance; performs more efficiently using an adaptor instead of a classification tool	Identify and recognize inappropriate actions performed by malevolent nodes; enhance the precision of vehicle geolocation data; optimize the process of transferring control between vehicles and RSUs; improve prediction accuracy, stability in predictions	Leads to computational complexity, potentially affecting the ability to interpret real-time data in dynamic traffic settings
Linear Regression	Simple and estimates the value of unfamiliar data by utilizing another correlated and familiar data value; calculates coefficients	Calculate journey time; important for designing routes, managing traffic, and enhancing overall productivity	Limited accuracy in predicting complicated networks; may not maximize radio usage efficiently
Logistic Regression	Calculate the probability of a scenario happening or a categorical variable; easier to manage multiple explanatory variables simultaneously	Improve the identification; analysis of message logs	Limited to binary outcomes; Selecting a model is difficult; requires knowledge; overfitting with multicollinearity

3.1.3. Reinforcement Learning (RL)

RL is a framework where agents or controllers enhance their actions during interactions with their environment. It maximizes total reward by connecting states to actions via reinforcement signals. In contrast to typical ML algorithms, learners are not given pre-

determined actions. Rather, RL involves trial and error to determine which activities yield the best reward. RL stands out from other algorithms due to its unique actions. They involve trial-and-error investigations and postponed reward calculations. Improved learning algorithms usually include four key components: policy, reward function, value function, and environment. The ML paradigm teaches an agent how to operate locally and decide how to optimize the overall benefit or minimize a cumulative penalty [76]. In contrast to the SL and UL paradigms, the error metric is time-dependent, and the temporal variable is decisive. Specifically, when compared to the supervised approach, RL operates without the need for annotated datasets. In response to the actions of the agent, the environment provides feedback. The RL structure is commonly composed of Markov Decision Support (MDS) systems, which employ dynamic programming techniques to optimize the incentive given. DNN-based frameworks that have substantially enhanced this learning approach have been developed lately [77,78].

Table 4. Unsupervised Learning: primary advantages, uses, and issues in the VANET domain.

ML Types	Advantages	Uses Areas in VANET	Issues
K-means	Beneficial in concealing secret information related and operators; does not require labeled information	Enhances cluster stability in VANET approaches based on clusters; creation of cryptographic algorithms to improve the security	Not capable of determining the optimal number of clusters; maintaining cluster reliability; maximizing cluster similarities
Hierarchical clustering (HC)	Connectivity-based clustering model for grouping data points, connect geographically close to ones	Spatial and social proximity for the effective exchange in the cluster; deals with the complicated and ever-changing nature of V2V and V2I; boosts the effectiveness of data transmission, decreases overhead; network scalability	Stability problem
GMM	Arrange information into groups; probability distribution	Cluster vehicles based on mobility patterns and locations; detect anomalies and misbehaving vehicles; predict future locations and trajectories	Less efficiency and longer delays in real-time software; overfitting issue; sensitivity to noise
MC	Autonomous systems with transparent states	Ability to monitor, gather, and disseminate data regarding traffic, driving conditions, and potential dangers	No history maintenance; future prediction
HMM	Used for autonomous systems with partially transparent states	Describe the connection between observations and hidden states that cause them	Restricted accuracy
PCA	Decreased information density	Reduce dimensions and lessen operational overhead; capable of reducing dimensionality, predicting Denial of Service (DoS) attacks and identifying driving hazards; optimizing buffering of multimedia contents	Low interpretability of principal components; outliers; affecting network performance and reliability
AR	Identification of basic correlations and faults quickly	Identify and recognize road incidents; produce routes and locations	Difficult to find the optimal number of clusters, maintain reliability, and maximize cluster similarities

The agent analyzes state St at each step t and selects an action A_t in action space A. The new state arrives after the object obtains a scalar reward R_t that signifies the standard of the action selected and advances to the subsequent one. The RL method tries how to relate this mixture of situations (St, At) from states to the best possible operation, which is

an estimate of the long-term benefit of staying in this position. The process by which an RL agent learns has been illustrated in Figure 5.

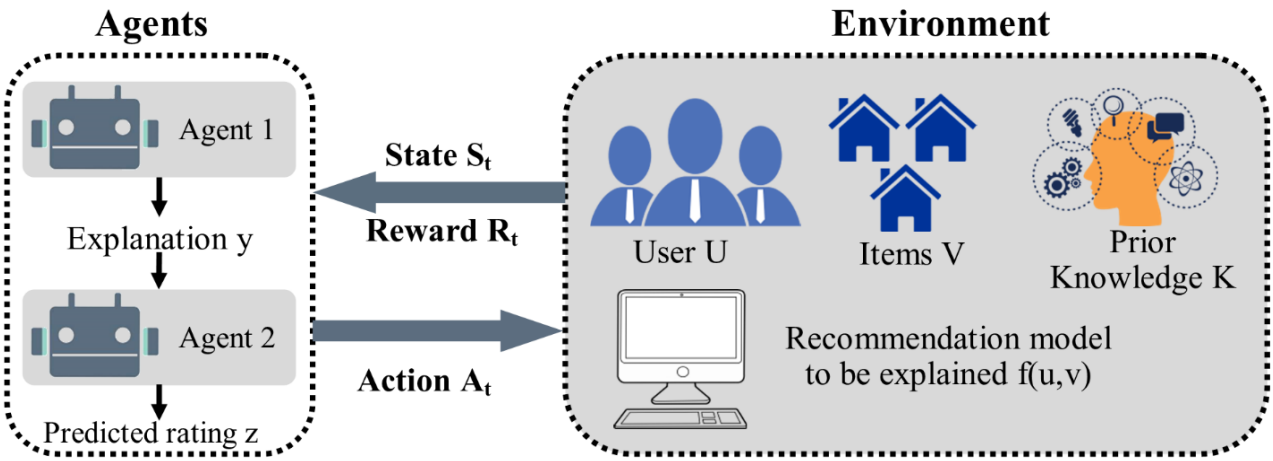


Figure 5. The Reinforcement Learning framework.

The responsibility of mapping conditions to actions performed by the agent lies with the policies. The reward function evaluates the current settings and allocates rewards or penalties based on the result obtained from the function. There exist two distinct variations of the value function, i.e., state-value and action-value, which calculates the long-term expected reward based on the agent's future state. The environment refers to a task or simulation in which the agent utilizes the trial-and-error mechanism to maximize the cumulative reward. An agent engages in interactions with its surroundings, acquires knowledge of its own and the environment's states, and continuously acquires and assimilates data to execute specific actions within an RL algorithm. Therefore, at each instantaneous moment, it discerns the precise condition of the surroundings and implements a course of action that prompts the environment to transform into a different phase. The agent operates under a reward–punishment framework that depends on the result of the action it selects. At this juncture, the action will be rewarded if it is beneficial. If the action is improper, a penalty will be assessed. Although this feedback is less enlightening than Supervised Learning, which provides appropriate actions, it is more informative than Unsupervised Learning. Using trial and error, this technique enables the agent to ascertain accurate actions, devoid of any explicit critique of its efficacy [27].

RL refers to a specific class of ML tasks that aim to systematically discover optimal solutions using recurrent experiences, as described in Table 5. In contrast to supervised and Unsupervised Learning, RL is characterized by its collaborative and iterative nature. The method explores various approaches, monitors the environment's response, and adjusts its actions to determine the optimal solution. Hence, RL has demonstrated significant benefits in the management of offloading for systems that have been installed with 5G/6G technologies [79], including spectrum allocation, implementation of proactive radio resource control, and the optimization of handling data distribution inside the established framework of network slicing [80]. The process of selecting actions in RL is intrinsically linked to a persistent challenge called the "trade-off between exploration and exploitation". By this trade-off, an agent is tasked with determining whether it is more advantageous to arbitrarily examine the environment in search of an action that will lead to further action or to maintain the existing data and optimize the rewards by selecting specified actions [81]. Deep deterministic policy gradient (DDPG), Trust Region Policy Optimization (TRPO), deep Q-learning, and deep double Q-learning are widely applied RL techniques in various applications.

(i) Q-learning (QL) is a model-free RL technique that instructs an agent on an action strategy based on environmental perceptions and status. The approach, despite being a model-free RL, excludes the transition probability. Beginning with the current state, the approach functions within an MDS paradigm to determine the optimal policy by utilizing an expectation-maximization algorithm on the average benefit estimated over all subsequent stages [82].
(ii) The double Q-learning (DQL) approach is an adaptation of Q-learning that explicitly tackles the problem of action value overestimation in noisy circumstances, resulting in a deceleration in the process of acquisition [83].
(iii) The Markov Decision Process (MDP) technique is a stochastic process that occurs in discrete time. It adheres to this Markov property; it can be argued that the probability of transitioning to a particular state in the upcoming time step is exclusively influenced by the present state. It endeavors to identify a practical course of steps for the decision-maker impacted by the ambient environment [26].
(iv) A deep Q-learning network (Deep QL) is used to address the issues of several states and large amounts of knowledge, and deep Q-learning [84] uses DNN instead of MDS architecture. Instead of using the standard Q-table to record states, actions, and predicted rewards, an ANN may instead predict the action and Q-value from the state. Because of its inherent developmental nature, most approaches rely on RNNs, LSTMs, GRUs, and CNNs [26,85].

Table 5. Reinforcement Learning: primary advantages, uses, and issues in the VANET domain.

ML Type	Advantages	Uses Areas in VANET	Issues
RL	Acquire knowledge through the process of experimentation	Highly efficient for complex vehicle mobility, driving prediction, and routing concerns; enhances Smart Vehicle Task Offloading for 5G/6G networks; enhances radio and wireless resource management	Requires massive amounts of data; high processing power; quantity of features

3.1.4. Semi-Supervised Learning

Semi-supervised Learning (SSL) is a specialized domain in ML that includes Supervised and Unsupervised Learning methodologies. This approach utilizes labeled and unlabeled information in AI models to achieve various objectives, such as classification and regression. SSL requires ensuring the unlabeled instances used for the training phase are pertinent to what the model has been learned for. SSL necessitates that the given data's distribution, p(x), includes knowledge of the posterior distribution, p(y | x), that denotes the probability of a given data point (x) belonging to a particular group (y). An investigation conducted in 2018 on SSL algorithms revealed that augmenting the volume of unlabeled knowledge tends to improve the efficacy of SSL approaches [86].

Improving prediction accuracy and making ML solutions work for more complicated tasks requires a large quantity of training data. Although small ML models may be developed with relatively small datasets, developing larger models like neural networks requires exponentially more data as the number of parameters increases. Distributing the ML burden across numerous machines and transitioning from a centralized to a distributed system used for learning information processing has outstripped the rise in the computation capability of computing gear. Distributed ML uses technologies like 5G, edge computing, and federated learning to make VANETs more innovative and resilient to support next-gen mobile apps that enhance security, productivity, and user experience.

3.2. Deep Learning

An AI subfield is DL, which evolved from Machine Learning. Its primary goal is to learn new things by analyzing large datasets. Due to their effectiveness, these approaches have found widespread application in various practical settings. Table 6 introduces the main DL methods, their advantages, and how they might perform in VANET networks.

3.2.1. Convolutional Neural Networks (CNNs)

CNNs are well known due to their simplicity and efficiency [87]. Computer vision CNN-based algorithms make this AI technique particularly successful for multimedia data assessment, like analyzing video for overcrowding and tragedy forecasting. It aids in identifying traffic signs and the identification of pedestrians or hazards via collected pictures. Nevertheless, it may also be utilized for 5G/6G resource control by ensuring the legitimacy of vehicle nodes and using Blockchain-based security measures [88].

3.2.2. Recurrent Neural Networks

RNNs tend to be well suited for uses involving information, primarily for interpreting temporal patterns like producing signals and training. This tool is highly effective for facilitating the interchange of knowledge in the context of integrated edge, fog, and cloud computing methodologies, and RNNs exhibit their highest efficiency when handling distinct and consecutive information. Furthermore, they could offer an effective method for mobility estimation by calculating the likelihood that an automobile will reach a specific area in the coming time, according to its current route, and by utilizing information acquired from the statistical evaluation of the information entered. By anticipating the accuracy of the incoming signal series, an RNN might prove advantageous in identifying the appropriate time to execute handovers. Additionally, by deriving available resource trends according to the frequency band utilization time, it can serve as a beneficial resource allocation utility [89]. Additionally, the analysis of the highway pictures recorded can be employed to identify obstructions on a highway utilizing an RNN.

3.2.3. Long Short-Term Memory (LSTM)

LSTM is a type of RNN architecture employed in DL. LSTMs include feedback links. They can handle discrete data and continuous streams of content. For instance, LSTM can be used for activities like speech recognition or non-segmented or connected handwriting recognition. Since significant occurrences in a period may occur at intervals of an uncertain time frame, there is a need for methods that excel at analyzing, predicting, and classification tasks involving time series data. LSTMs were created to solve the problem of the difficulty in learning lengthy sets of data caused by the challenge of vanishing gradients. Parameter modification becomes insignificant when the gradient declines, suggesting that no significant learning occurs; gradients communicate data utilized to modify the RNN variables [43].

3.2.4. Gated Recurrent Units

An RNN has a major issue with its short-state memory and gradients; it cannot store the data for a long period. Recurring connections and storage multiplicate modules address these issues [90]. To address the issue of regular RNNs potentially leading to the elimination of the gradient, gated RNNs originated.

3.2.5. Deep Auto-Encoders (Deep AEs)

A Deep AE is a UL technique that extracts essential properties from networks' admission information. Regeneration involves training a neural network to estimate feed at the outcome from a hidden layer. The objective of it is to reduce reconstruction error [91].

AEs assist in acquiring characteristics and reduce size by removing unnecessary elements. These methods can anticipate traffic jams by identifying temporal correlations of vehicle communication. DAE reduces transport size to extract helpful information for attack predictions and identification. Such characteristics can provide information for classifications to differentiate routine activity against threats. It can estimate vehicle accelerations by analyzing the velocity using prior data [92].

3.2.6. Restricted Boltzmann Machines (RBMs)

RBMs are a technique for dimensionality reduction, classification, regression, collaborative filtering, feature training, and phrase learning. Multiple limited Boltzmann machines can be stacked to generate improved deep networks. RBMs are based on Unsupervised Learning with feedback technology. Restricting Boltzmann machines can prove effective for communication forecasting by restoring prior data using combination and supervised nonlinear estimation. RBMs may identify vehicle infiltration in V2X by fitting vehicle attributes from supplied patterns using UL classifiers. This approach adds to the collection of past vehicle actions and characteristics from prior data inputs. Temporal and spatial relationships between mishap occurrence and traffic movement might reduce highway capacity. This approach can forecast incident time by analyzing ongoing vehicular conditions and creating sequences utilizing classification [93].

3.2.7. Deep Belief Networks (DBN)

DBNs have a significant number of secret levels. Using DBNs for 6G VANET privacy is advantageous due to their recursive encoding of features, which may forecast operator moods and trip duration, rendering them safer than standard VANETs. Vehicular information from roadway scenarios can be divided into multiple basic source spaces. Following that, a DBN trains every record entry, and the combined algorithm generates the forecasted predictions. DBNs avoid Blockchain attacks in VANETs by reducing the variety of positive and fraudulent vehicles, messages transmitted, and riddle computing time [94].

3.2.8. Generative Adversarial Networks (GANs)

GANs are AI techniques capable of accurately replicating photographs and other information. They minimize delays in communication and enhance entertainment app performance by using specified repeats to create patterns. Highly successful resource assignments could be obtained by tailoring resources to every vehicle application's demands. A GAN utilizes roughly semantic locations to enhance pattern estimation, captures semantics like combining and shifting, and controls vehicular trajectories [95].

3.2.9. Ensemble of Deep Learning Networks (EDLNs)

Multiple DL models can collaborate to provide superior performance compared to when DL techniques are utilized individually [96]. EDLNs can be accomplished by grouping intellectual, exclusive, or mixed approaches. EDLNs are likewise used to handle intricate issues with high-dimensional attributes and uncertainties [97]. The architecture consists of several sequential phases of classification methods that may exhibit homogeneity or heterogeneity in a specific category. EDLNs often facilitate the inclusion of diverse elements and the broad application of the framework [98].

3.2.10. Deep Reinforcement Learning (DRL)

DRL is a distinct classification of Reinforcement Learning that combines ANN with RL methodologies. Its purpose is to enable Software-Defined Networking (SDN) entities to obtain insights into the most efficient [99]. It can convey procedures utilized in an extensive input data space by synthesizing a sequence of classifiers [100]. The conclusion

is reached via a series of phases of experimentation and learning from mistakes. The user chooses a procedure within the state space from the available choices. DRL can operate without previous awareness of what was entered into and remains efficient despite adversarial circumstances, such as data qualities that may introduce semantic or logical disputes. It proves useful for controlling congestion, allocating resources, enhancing network accessibility, and selecting transmissions for interconnected navigation. It achieves this by training the framework using earlier observed information and choosing elements utilizing information acquired by the prior highway conditions [101]. It is also utilized to identifying distinct attacks with great precision [102].

Table 6. DL methods: primary advantages, issues, and uses in the VANET domain.

DL Types	Advantages	Uses Areas in VANET	Issues
CNN	Capable, simple, and highly effective	Accident forecasting involves analyzing videos and multimedia data; managing resources using 5G/6G technology	Implementing CNNs in resource-limited vehicles for assisting vehicular networks is tough
RNN	Maximum efficiency for discrete and sequential data	Utilizing collaboration edge, fog, and cloud technology to exchange information; improves the identification of barriers and forecasting of mobility	Occurrence of abrupt and disruptive changes in gradients
LSTM	Recognize long-term dependencies; capacity to acquire and retain knowledge of extended relationships or connections	Forecasting vehicular traffic for route selection	Complex training increases computational overhead [103]
GRUs	Retain knowledge over extended periods and discard useless data	Effectiveness in traffic prediction and intrusion detection; utilizing temporal-based prediction properties to detect prospective threats.	The presence of intricate geographical and temporal correlations in traffic flow data poses a difficult challenge
Deep AE	High level of accuracy for identifying malicious activity, i.e., spoofing, flooding, and replay attacks.	Traffic prediction; proficient in conducting attack prevention and identification; able to calculate the velocity of vehicles	Higher processing duration and utilization of resources [104,105]
RBMs	Efficiently encode intricate datasets; removing noise from data	Prediction of network traffic; recognize unauthorized breaches; forecast the duration and area of road accident	Not efficient for modeling natural images
Deep Belief Encoder	Iterative visualization of features	Ensuring the security of 6G VANETs; capable of accurately predicting operator sentiments, journey timing	High processing duration and exploitation of resources
GANs	Predetermined total iteration defines sample	Minimizes the delay in communication; ability to anticipate the path of a vehicle; enhances the efficiency of infotainment programs	Stability problems during training, interpretability issues
EDLN	Facilitates the inclusion of diverse elements and allows for broad application of the model	Capability to identify Distributed Denial of Service (DDoS) attacks and Blockchain attacks; forecast the movement of transportation and offer precise GPS locations to enhance the flow of data	Unable to solve complicated issues related to real-life vehicle situations
DRL	address intricate, acquiring knowledge through expe-rience, managing uncer-tainty and noise of network	Traffic management encompasses routing, congestion mitigation, traffic signal optimization, and autonomous vehicle navigation; efficacy and security	Predicated on numerous assumptions that are challenging to realize in practice

3.3. Swarm Techniques (STs)

The combined actions of autonomous and dispersed systems are known as swarm intelligence. In a VANET, this involves an ensemble of vehicles communicating with others and the outside world. Since there is no centralized system, cars follow fundamental standards like highway architecture, speed limits, and signals. Swarm cognitive abilities consist of ant behavior, bacteria germination, bird groups, fish schools, and microbial cognition. The swarm methods are described as follows, and the advantages and issues in vehicular networks are discussed in Table 7:

(i) Particle Swarm Optimization (PSO): It is a comprehensive optimization technique that may solve problems with an individual point or entire area in a space with n dimensions. It ensures each atom chooses its preferred prior location or goes towards another one based on velocity if the latest location is superior [106].
(ii) Ant Colony Optimization (ACO): Graph optimization challenges of all kinds are searched for the nearest possible optimum solutions by ACO. The ants within the algorithm strive to adhere to the shortest path, as described in reference [107].
(iii) Stochastic diffusion search (SDS): The method was initially developed for a population-based mapping tool. It utilizes immediate interaction methods to assess the identification and aggregating hypotheses of all potential routes, including collaborative behavior observed in insect societies [108].
(iv) Artificial Swarm Intelligence (ASI): This refers to the collective intelligence exhibited by a group of artificial agents working together in a coordinated manner. It is an on-demand network that connects integrated human participants in distant groups. It utilizes swarm intelligence (SI) and AI techniques to balance and analyze the network using natural swarms. AI-based ASI creates a collective intelligence of human participants, enabling groups to reach results with implications exceptionally pertinent to what humans can do independently [109].

The vast majority of swarm intelligence techniques do not involve the formulation of hypotheses about issue optimization. Moreover, using swarm intelligence facilitates the identification of methods of higher standards through the integration of path optimization and the harnessing of innate knowledge. Furthermore, swarm intelligence is renowned for its simplicity and straightforward deployment compared to alternative AI methodologies. Swarm intelligence is frequently utilized to facilitate routing optimization, including tasks such as determining the shortest path, engaging in geocast routing, and implementing clustering methods [110].

Table 7. Swarm methods: primary advantages, issues, and uses in the VANET domain.

Swarm Types	Advantages	Uses Areas in VANET	Issues
PSO	No assumptions are necessary for the optimization of the problem	Optimizing routing protocols, i.e., shortest path, geocast, and clustering	Insufficient coverage and inefficient allocation of resources caused by overlapping coverage in RSUs [111]
ACO	Gradient information is not necessary for problem efficiency	Identify and recognize nodes that are intended to cause harm	Efficient and reliable multi-hop relaying routes that operate in real time; challenging task of adjusting parameters due to their great complexity [112]
SDS	Uses a combination of path discovery and AI for high-quality solutions	Handles traffic congestion	Signal reception and routing efficiency are hindered (confined mobility, irregular node distribution) [113]
ASI	Straightforward, and effortless to execute	Assists in mitigating routing attacks; contributes to the optimization of routing	Complex behaviours and interactions; congestion overhead

4. Simulation Tools

Different simulation tools are employed to assess the efficiency of vehicular networks and analyze the protocols. Simulation tools are employed to accurately reproduce the real-world behaviors of a VANET system and evaluate the effectiveness of various strategies under different conditions. These became known as crucial instruments for educational studies and industrial ventures. The basic components of contemporary VANET simulators are their mobility and network elements. The mobility model accurately represents the real-life actions of vehicles in traffic. This technology is mostly employed for imitating the precise motion patterns of automobiles. To mimic the transmission of data between associated nodes, a network simulator is employed. In the VANET, the network typically consists of vehicles and RSUs and primarily relies on wireless connectivity. It is desirable to replicate every aspect of the network, including the entire protocol stack [114].

NS-3 is a widely used open-source network simulator specifically employed for simulating VANETs. NS-3 provides an all-inclusive resource for simulating and studying network protocols. It is a versatile, customizable alternative that offers outstanding versatility and adaptability. NS-2 is a more antiquated network simulator than its predecessor, NS-3. NS-2 provides an extensive collection of network models and protocols. However, its usage can be challenging because it is implemented in the C++ programming language and possesses an intricate architecture. Objective modular network test-bed in C++ (OMNeT++) is a popular open-source simulation framework extensively utilized for conducting VANET simulations. The software has an extensible structure and provides extensive tools for modeling and simulating different protocols. Optimized network engineering tool (OPNET) is a proprietary network simulation tool well suited for industrial applications. It is notable for its visually appealing user interface and intuitive usability. OPNET provides comprehensive modeling and analytics features for evaluating network performance, enhancing the usage of assets, and improving productivity. Nevertheless, due to its business-oriented nature, the expenses associated with obtaining a license can be substantial. Such network simulation programs are crucial for scholars to examine VANET protocols, devise novel techniques, and assess network efficiency in VANET simulations. Every simulator possesses unique benefits and drawbacks [115–117]. SUMO, or Simulation of Urban Mobility, is an open-source traffic simulator that handles massive traffic volumes. SUMO assists in preventing vehicle collisions, accommodating various types of vehicles, facilitating traffic movement, and regulating speed, among other features. It can import and modify various mobility maps. SUMO employs a graphical user interface (GUI) to direct traffic across individuals and many vehicles efficiently. This software is compatible with NS2, NS3, and OMNeT++. MOVE is a GUI that is built on top of and extends SUMO. Writing simulation scripts to replicate the environment is a time-saving practice. MOVE is a software tool that is capable of modifying maps. It may be integrated with other simulators, such as NS2 and GloMoSim, to simulate global mobile information systems [118]. Table 8 provides the advantages and disadvantages of specific commonly utilized mobility and network simulation tools suitable for vehicular ad hoc networks.

Table 8. Commonly used simulation tools.

Simulators	Simulator Type	Licensed	Written in	Language Support	Advantages	Disadvantages
NS2 [119]	Network Simulator	Open Source	C++	OTCL/C++	Used by substantial customer and developer communities	Difficult to learning

Table 8. *Cont.*

Simulators	Simulator Type	Licensed	Written in	Language Support	Advantages	Disadvantages
NS3 [120]	Network Simulator	Open Source	Python, C++	C++	Open source and offers a substantial customer society	Less efficiency in massive amount simulations; increased processing capacity that is necessary
MATLAB/Simulink [121]	Network Simulator	Open Source	C/C+, JAVA, FORTRAN	C/C++, JAVA, Python	Extensive combination features and wide range of computational functions	Encounter difficulties with efficiency
OMNeT++ [122]	Network Simulator	Open Source	C++	C++	Substantial customer base and a highly engaged developing organization. Support GUI	Possessing a steep learning curve
OPNET [123]	Network Simulator	Open Source	C++	OTCL/C++	Effectiveness and visualization	Expensive price of licenses can be attributed to their business nature
VANETSim [121]	Network Simulator	Open Source	JAVA	JAVA	Capability to replicate a range of circumstances, including varying levels of traffic statistics, differing roadway circumstances, performance restrictions, and the flow patterns of vehicles	Cannot precisely correspond to practical outcomes
VANET Toolbox [121]	Network Simulator	Open Source	MATLAB, C++	MATLAB, C++	Toolbox offers the ability to represent and examine simulated outcomes visually	Certain specialized techniques or sophisticated analyses may necessitate supplementary capabilities.
MOVE [118]	Traffic Simulator	Open Source	C++	C++, JAVA, FORTRAN	Offers a range of methods and models to simulate the motion and interconnections between automobiles accurately	Assist in integrating using additional applications and processes
SUMO [118]	Traffic Simulator	Open Source	C++	Python, C, C++	Valuable for simulating transportation patterns and relationships, i.e., highway situations, traffic movement, and lights	Visual interface of SUMO is constrained and unsuitable
Veins [114,124]	Network Simulator	Open Source	C++	C++, Python	Developed explicitly for simulating vehicular networks; open-source framework based on OMNeT++ and SUMO; encompasses extension for many protocol stacks	SUMO and OMNeT++ are installed and running correctly; any imperfections among these components may lead to veins producing inconsistent results

Table 8. *Cont.*

Simulators	Simulator Type	Licensed	Written in	Language Support	Advantages	Disadvantages
Simu5G [12]	Network Simulator	Open Source	C++	C++, Scripting Language	Network slicing; 5G use cases; visualization and debugging tools	Manual configuration; limited to network simulations; steep learning curve

5. AI-Powered VANET Solutions

This section examines seven fields that might profit from implementing ML technologies. These fields include applications, security, routing, resource management, mobility management, integrated architectures, and clustering, as shown in Figure 6.

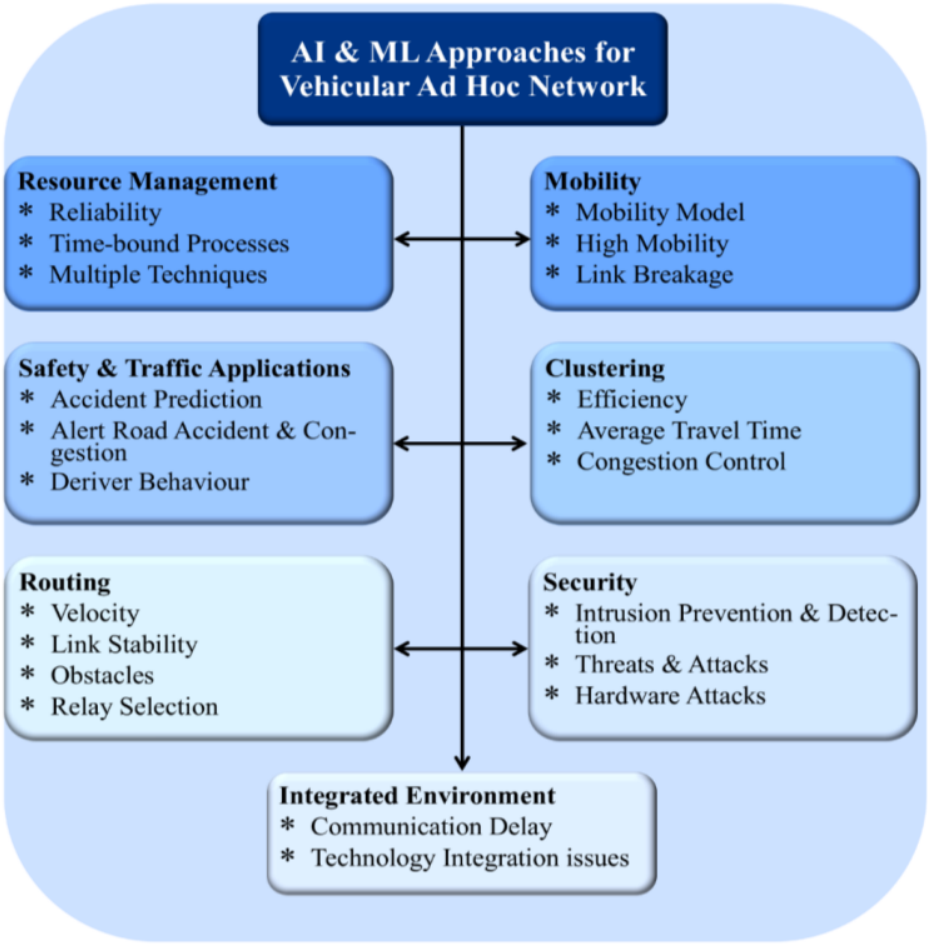


Figure 6. AI and ML approaches for vehicular ad hoc network.

5.1. Safety and Traffic Applications

Safety Management vehicular ad hoc network apps are utilized to mitigate car collisions by distributing relevant data regarding potential hazards and obstacles. The utilization of Random Forest algorithms [125] aids in the prediction of crashes. Motorists must consider variables such as traffic signals, pedestrians, and GPS navigation. SVM and CNNs [126] detect highway conditions and forecast drivers' behaviors. Safety applications are employed to manage safe lane changes, facilitate navigation, and implement automatic emergency braking [127]. PCA approaches are used to obtain important data entries [128], while NB and DT-based solutions are employed to make appropriate judgments and decrease traffic congestion [129].

Traffic management: The fundamental goal of traffic control and monitoring is to improve traffic flows, reduce transmission times, and give consumers real-time data regarding road circumstances [130]. RL methods can be employed to manage digital signal components and traffic lights efficiently [131]. GRU, a variant of RNN, can forecast local traffic flow volume using less complex gating mechanisms and requiring fewer processing resources [132]. The use of LSTM [133] can enhance the accuracy of traffic forecasts and optimize data fitting. The utilization of ACO swarm intelligence can effectively direct traffic flows to minimize congestion [134]. The CNN- or ANN-based methods provide superior prediction skills with a greater level of accuracy [133,135]. The KNN algorithm can forecast the speed and density of vehicles at various periods throughout the day [136].

Infotainment applications: VANETs are widely used for providing different amenities related to convenience, entertainment, and highway security applications. According to research, infotainment services, such as the exchange of multimedia content and movies, are widely favored [137]. Seamless Internet connectivity is crucial for users of VANET [138,139], and the inclusion of entertainment features such as advertisements and parking availability improves the impression [140]. CNNs are highly suitable for the analysis of video and image information [141]. On the other hand, deep auto-encoders can improve file compression to adaptive compression of multimedia files [142]. The PSO technique can manage trip path direction by generating near-optimal paths using routes [143].

5.2. Security

The security of VANETs is of paramount significance due to their continuous transmission of messages between vehicles and roadside facilities [144,145]. The content of these messages is sensitive and crucial to ensure the preservation of reliability, genuineness, secrecy, and message privacy. Additionally, factors such as data integrity, trust level, relevance, and real-time safety-related applications are crucial to consider [145]. Dissemination of false or inaccurate information regarding the vehicle's situation, road accidents, and conditions may also provide potential security threats [146]. Key security problems include malicious vehicles, Distributed Denial of Service (DDoS) assaults, authentication vulnerabilities, SQL injections, anti-intrusion measures, and physical attacks. Security challenges in VANET include SQL injections, attack protection, and physical assaults [147]. The k-means [148] approach is especially well suited for identifying harmful nodes since it can easily adjust to the changing structure of VANET. Effective management is necessary for internal attacks, precisely CAN threats. The GRU defines a specific sort of RNN that can be utilized in intrusion detection. However, it is essential to combine it with additional methods using DL [149]. A GRU system establishes a decentralized collaborative framework that assesses network conditions and promptly initiates appropriate measures to defend against jamming attacks [150]. An ANN effectively detects misbehavior [151], whereas a CNN retrieves spatio-temporal features of vehicles [152] from a two-dimensional dataset. LSTM can enhance intrusion detection by autonomously identifying malicious network traffic on the OBU using time-dependent traffic flow data [153]. Trust management systems in VANETs guarantee the reliability and credibility of both information and data nodes. Evaluating the reliability of crucial communications, such as urgent warnings, is intricate and demanding. SVM and Reinforcement Learning might be employed in VANETs to develop trust strategies for the actions of vehicle nodes or third parties. SVMs are reliable ML techniques commonly used in nonlinear classification scenarios [154]. In contrast, the concept of Reinforcement Learning can effectively handle the vast volume of data generated by automobiles [155]. Particle Swarm Optimization can reduce Denial of Service (DoS) assaults by analyzing the collective behavior of vehicles [156]. PSO is a computational algorithm that simulates the dynamics of particles inside a search space. It

adjusts the particles depending on their historical behaviors, using a heuristic technique that simulates the flight of bird flocks.

5.3. Routing

Routing is essential in VANETs since all supported services depend on multi-hop network architecture for transferring data [157]. Fluctuations in speed in urban and highway settings might lead to regular breakdowns in the network connectivity, presenting a significant obstacle to sustaining uninterrupted communication [158]. To establish effective interactions in routing protocols, especially ones that include multiple hops, it is necessary to choose relays that are quasi-optimal. The utilization of Random Forest, SVM classification, and LSTM algorithms can enhance routing protocols in the vehicle environment [159]. LSTM, in particular, plays a vital role in guaranteeing the dependability of vehicles of decisions regarding routing by making stochastic predictions of traffic movement [160]. Researchers conducted a study on driver behavior and discovered that CNN [161] is highly efficient at forecasting driving routes and preventing sudden alterations. Ant Colony Optimization (ACO) is an effective approach for finding quasi-shortest paths in data routing [107]. Additionally, the DT [48] and NB [129] methods are also valuable in this context. ACO exhibits self-organizational properties and demonstrates resilience in the face of errors. Particle Swarm Optimization is a vital component of geocast protocols since it directs the migration of particles toward the most optimal places [162].

5.4. Resource Management

Distributing services fairly in VANETs is challenging [163] because of several intrinsic difficulties. This encompasses inaccurate and overcrowded wireless channels, increasingly fragmented and overloaded bandwidth, equipment deficiencies, and the ongoing proliferation of vehicle communication systems [164]. The diverse nature of various connection techniques used in VANETs adds complexity to their incorporation with each other and outside systems, making it a more difficult task [165]. However, the application of DRL has the potential to be exceedingly effective in resolving these particular difficulties through the integration of intelligent cloud technology utilization methods. It can enhance job scheduling and transfer workloads from inside to outside resources, hence mitigating traffic on physical pathways [166]. Furthermore, the integration of 5G and LTE technologies can enhance the utilization of resources in VANET using DRL [165]. DRL can effectively handle resource allocation challenges by breaking difficult issues into smaller ones. The principle of network slicing represents a novel architectural approach to facilitate the consolidation of virtual and separate computational systems into a unified real-world environment. The SVM technique [167] could be utilized to create efficient techniques for network slicing, encompassing the acquisition of features and classification.

5.5. Mobility Management

The Internet of Vehicles permits dependable, low-latency, and high-bandwidth transmission. It exhibits a strong correlation between user portability and responses to barriers in complicated circumstances on highway frameworks, such as crossroads and traffic signs, and at RSUs located on highways or around an urban area. Significant impacts are observed on both the mobility concept and the overall efficiency of radio signals by such constraints [168]. The primary distinguishing feature of the vehicle is its high-speed mobility, which sets it apart from different cellular networks. Vehicle velocities may differ based on their surroundings [169]. While the motion of cars can be anticipated, the effect of motion on connection and network structure constitutes a significant obstacle in vehicular networks. As an illustration, a vehicle may swiftly join or depart from the community, resulting in regular modifications to the network's architecture. Formulating

approaches to effectively regulating drivers' actions is paramount in tackling mobility concerns. CNNs and ANNs are suitable AI approaches for driving patterns and highway congestion. ANN and fog computing can be utilized for predicting mobility, particularly in vehicular networks based on Software-Defined Networking (SDN) [170,171]. The KNN algorithm can forecast mobility and lane shifts by considering the nearness of one vehicle with comparable characteristics [172].

5.6. Integrated Architectures

VANET technologies necessitate a diverse set of connectivity and computational skills for their effective setup and installation. Recent technologies have been incorporated into VANET systems [173]. Integrating these heterogeneous networks and hybrid systems poses several challenges, mainly regarding the delay in analyzing information and the hazards associated with protection [174]. The data undergo multiple analyzing processes as they pass across various systems built inside VANETs. DRL has emerged as a highly effective strategy for effectively handling variety in data transport facilitated by the flexible characteristics exhibited by convolutional layers [175]. One potential application of GANs is the reduced latency in transporting information among various levels of an integration architecture. This is possible when GANs have a predetermined number of repetitions for creating an illustration approach, regardless of the dimension or form of the information [176]. The KNN algorithm provides a viable method for identifying breaches owing to its notable precision in both node classification and regression tasks. Nevertheless, the EDLN has been found to exhibit greater effectiveness due to its ability to accommodate diverse data sources and heterogeneous types of information [177]. Within the context of a cloud–VANET information flow situation, it is possible to generate two distinct EDLNs using previous ordinary streams and assaults. Subsequently, an additional classifier can be employed to obtain a feature vector representation [178]. The prediction step of the framework facilitates the anticipation and identification of novel hostile behaviors, thus allowing prompt sorting, cessation of aberrant behaviors, or prevention of harmful vehicle movement before the occurrence of novel attacks. VANET designs increasingly incorporate future technologies such as DSRC, IEEE 802.11p, and LTE standards [179,180]. SVM and CNN are robust AI methodologies that have demonstrated efficacy in enhancing medium control and assigning spectrum in diverse situations [50,181]. These algorithms cater to a wide range of information and enable nonlinear classifications and grouping even without annotated input data.

Clustering

The clustering process is a crucial application of V2X technology. It provides several advantages, including the mitigation of air drag, enhancement of fuel economy, alleviation of traffic jams, and reduction in traveling duration. The implementation of surveillance applications that utilize live video over V2X networks has the potential to enhance vehicle security and convenience by providing image information through the utilization of front and rear-view cameras. Nevertheless, the implementation of video streaming in vehicle platoons introduces novel obstacles, including the potential constraints on the spectrum of the primary vehicle transmitting data over the MAC layer in IEEE 802.11p. A cluster of moving vehicles is established through the collaboration of vehicles, wherein the cluster head (CH) functions as an internet connection that serves the collaborative group. Clustering algorithms must meet the IoV communication performance requirements while identifying and documenting abrupt alterations in mobility, network, and cluster behavior [101,168,182]. The clustering process utilizes the k-means algorithm; included in this analysis are the distance, direction, signaling magnitude, trustworthiness, and category

of communications [52]. An agglomerative hierarchical clustering method incorporates factors such as velocity, direction, and specific QoS parameters to organize data into clusters of vehicles [68]. Standard procedures for initiating the clustering process involve peer detection, cluster head selection, affiliation, announcement, and maintenance. A learning algorithm [46,183] in which agents determine traffic behavior and velocity at intersections selects cluster heads (CHs) based on vehicle relative velocities. GMMs and k-means algorithms enhance the cluster's stability inside an extremely volatile setting [7,70,183]. In the fuzzy logic system (FLS), a level of certainty is considered rather than just using the values true or false. A learning factor is introduced for rewards with positive results and penalized or decreased for negative results. This mechanism progressively finds the best CH selection strategy. Fuzzy logic uses relative velocities between vehicles as CH selection criteria and driver intentions to assess eligibility [184].

AI is a promising approach for planning, scheduling, and optimizing these issues. Some of the AI and ML techniques used with VANETs are described in Table 9, which can solve specific problems. Fuzzy-logic-based algorithms can provide better stability than ML algorithms that predict the future movement of the vehicle. As a result, hybrid algorithms that combine ML algorithms with fuzzy logic algorithms can provide better stability than ML algorithms [184].

Table 9. Use of AI and ML approaches in vehicular network to solve issues.

Vehicular Applications	**Issues**	**Techniques Used**
Safety and Traffic Applications	Specific Field: safety, traffic, infotainment - Anticipating and notifying users about accidents, forecasting driver conduct, and detecting movement patterns - Mitigate traffic bottlenecks following a collision - Maneuvering between lanes, velocity, and regulation of traffic jams - Transmission of audio and visual information, ensuring high-quality video and supporting QoS for run-time applications.	RF [25], CNN [126], PCA [128], SVM [128], NB [129], DT RL [131], GRU [132], CNN [133], LSTM [133], ACO [134], ANN [135], KNN [136] CNN [141], DAE [142], PSO [143]
Security	Specific Field: physical, network, application, and cloud layers - Malevolent intent vehicle - Authentication and governance of trust - SQL injection - Attack detection and prevention	KNN [148], GRU [149] ANN [151], CNN [152] SVM [154], RL [155] GRU [150], PSO [156], LSTM [153]
Routing	Specific Field: continuous communication for optimal routing - Factors affecting the velocity of vehicles - Interruptions of communication challenges, - Decision of signal-relaying stations	ACO [107], SVM [159], DT [48], NV [129], LSTM [160], PSO [162]
Resource Management	Specific Field: resource management, access methods - Postponement for susceptibility - The resilience of vehicle apps is an essential element of RSUs and OBU - Comprises various tools, i.e., 4G LTE, 5G, and 6G	DRL [165,166], SVM [167]
Mobility	Specific Field: fast mobility; driving patterns, traffic - Modelling of mobility - Transmission in highly mobile scenarios - Interruption of connection	CNN [169], ANN [170], KNN [172], GRU [132]

Table 9. *Cont.*

Vehicular Applications	Issues	Techniques Used
Integrated Architecture	Specific Field: emerging technique computation - Latency in communication - Combination of emerging techniques	DRL [175], GAN [176], EDLN [177], CNN [180], SVM [181]
Clustering	Specific Field: formation, maintenance - Modifications in mobility, network, and cluster topology, specifications for QoS, identification of neighbors, selection of cluster heads (CHs), membership, announcement, maintenance, reliability, and stability	NB [52], K-means [66], HC [68], GMM [7,70,181], fuzzy logic [184]

6. Future Challenges and Research Scopes

The normal brain may struggle to comprehend how AI makes judgments according to unknown factors. Algorithms for AI must be created and instructed with a focus on preventing the occurrence of unintended consequences, particularly in domains outside its intended scope. Ultimately, it is imperative to evaluate the user's endorsement of the incorporation of AI into the vehicular network, specifically regarding its applications and utilization within this domain. These strategies give rise to certain current and potential future problems, which will be explored below.

6.1. Limitations of ML Techniques in VANET

- ML approaches can be utilized in the vehicular network setting; however, they encounter constraints such as significant memory demands and complications [185].
- SVMs show potential but encounter obstacles related to selecting an efficient kernel and managing the complexities of models.
- The adaptation of neural networks to VANETs is constrained by certain restrictions, like understanding feature independence and the occurrence of the "zero frequency" scenario. Due to the individualistic approach toward features, NB cannot derive significant insights from the interconnections across the parameters it sets [186]. Nevertheless, in scenarios when samples have correlated and comparable characteristics, it can function with precision.
- KNNs might be lengthy and intricate in a vehicular network [187].
- RNNs can tackle VANET difficulties but may lack efficiency in time-critical applications such as cybersecurity.
- AR methods exhibit prolonged process times and demonstrate worse efficiency than K-means, particularly in identifying prevalent risks.
- The primary challenge of utilizing EL is its more significant temporal overhead compared to alternative single-classifier-based techniques.
- PCA provides an approach utilized in neural networks to reduce the number of features effectively. This may be combined with additional methods of ML to improve efficiency.
- Reinforcement Learning necessitates substantial information and extensive computational resources [188], so its utilization in physical structures is constrained by the challenge of dealing with multiple aspects.

6.2. Limitations of DL Techniques in VANET

- CNNs possess significant computational burdens, rendering them appropriate for equipment with limited resources [189,190], such as cars.

- RNNs in VANETs encounter problems with overloading or overflowing while being trained, resulting in significant changes within the NN [191].
- Both LSTM and GRU models have limitations, particularly in VANET scenarios involving quick response times, and are affected by latencies. These negatives include heightened complexity and a significant demand for storage bandwidth.
- ANNs exhibit intensive training duration, and their development can be impeded if the experimental dataset is inaccurately portrayed.
- The lengthy learning period of RBMs makes it difficult for them to adjust to vehicle connections.
- DBNs have drawbacks since they require an extensive activation step and the necessity of embracing GAN learning [192].
- EDLNs in VANET can significantly enhance machine performance when integrating various mixed architectures [193].
- Distributed Reinforcement Learning, an approach in DL, involves multiple premises that are challenging to fulfill in practical scenarios, rendering it inappropriate for vehicular ad hoc network situations.

6.3. Limitations of Swarm Techniques in VANET

- Swarm behavior utilizing bio-inspired methodologies could impact the cooperation and interaction mechanisms of VANETs [47]. The methods employed can effectively address various challenges encountered in VANETs, such as route finding, scalability, resource demands, and signal diversity.
- Particle Swarm Optimization encounters security concerns in VANETs because of their unmonitored structure and the requirement for integrating different heuristics [194].
- Ant Colony Optimization necessitates significant computational power and extensive time computation to produce different results [195].
- Artificial Swarm Intelligence (ASI) leverages real-time communication and AI approaches to generate an integrated cognitive mechanism comprising human beings, forming a "hive mind" [196].
- The utilization of AI methods on vehicular networks encounters the obstacle of adjusting to novel V2X communication protocols.
- AI tools can improve the emerging V2X communication architecture by including highway and weather factors in planning data transmission, predictive methods, and assigning resources. Nevertheless, AI utilization must be cautiously approached at this stage with high standards.
- Ultimately, the research mentions energy-efficient AI/ML algorithms for future requirements. Recently, the proliferation of linked devices has significantly expanded, leading to applications where AI/ML operates on embedded gadgets. Such gadgets have minimal electrical consumption, yet AI/ML can generate computationally demanding tasks inappropriate for those gadget settings. Benchmarking AI/ML algorithms for energy efficiency is required when finding an appropriate solution for embedded devices. Also, a hybrid AI technique is needed to improve the adaptability and robustness of vehicular networks by minimizing the memory and computational overhead. It is also essential to convert the centralized system into a distributed one in order to share the ML workload over multiple computers since the demand for training data processing has outpaced the increase in computing devices' computational capacity. A cohesive model's construction and efficient training process parallelization are required for distributed systems.

7. Conclusions

This article comprehensively analyzes the relevant AI methodologies that may be employed in vehicular networks. It has elucidated many AI methodologies. AI-based methodologies have promise in augmenting the efficacy of automotive systems compared to traditional methods. The domains of Machine Learning, DL, and swarm techniques within AI can mutually reinforce one another to attain the most successful potential strategies that can tackle the limitations of ML, DL, and SI. Generally, AI algorithms incur greater computational expenses and need more resources. Embedding these objects inside automobiles or RSUs is prohibited. Nevertheless, the advent of novel combined designs and access methods, including cloud and edge computing, can potentially mitigate the computing burden associated with AI methodologies. This may be achieved by offloading specific calculations to outside servers on the edge or in the cloud. This article first examined the advantages of utilizing AI approaches intensely with vehicular networks and then considered the drawbacks that often come along with specific AI techniques.

Author Contributions: N.B., A.K. and P.K.S. conceived the plan to carry out the review work and designed a framework to carry out comparative analysis of different methods. V.K.M. and V.B. suggested the research idea. V.K.M., P.K.S. and V.B. reviewed this manuscript and improved its quality. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

1. Hajlaoui, R.; Guyennet, H.; Moulahi, T. A Survey on Heuristic-Based Routing Methods in a Vehicular Ad-Hoc Network: Technical Challenges and Future Trends. *IEEE Sens. J.* **2016**, *16*, 6782–6792. [CrossRef]
2. Nazib, R.A.; Moh, S. Routing Protocols for Unmanned Aerial Vehicle-Aided Vehicular Ad Hoc Networks: A Survey. *IEEE Access* **2020**, *8*, 77535–77560. [CrossRef]
3. Tong, W.; Hussain, A.; Bo, W.X.; Maharjan, S. Artificial Intelligence for Vehicle-to-Everything: A Survey. *IEEE Access* **2019**, *7*, 10823–10843. [CrossRef]
4. Qu, F.; Wu, Z.; Wang, F.; Cho, W. A Security and Privacy Review of VANETs. *IEEE Trans. Intell. Transp. Syst.* **2015**, *16*, 2985–2996. [CrossRef]
5. Meneguette, R.I. A Vehicular Cloud-Based Framework for the Intelligent Transport Management of Big Cities. *Int. J. Distrib. Sens. Netw.* **2016**, *12*, 8198597. [CrossRef]
6. Ansari, A.R.; Saeed, N.; Ul Haq, M.I.; Cho, S. Accurate 3D Localization Method for Public Safety Applications in Vehicular Ad-Hoc Networks. *IEEE Access* **2018**, *6*, 20756–20763. [CrossRef]
7. Kumari, A.; Kumar, S.; Raw, R.S. Advancing VANET Stability: Enhanced Cluster Head Selection with iTTM and Weighted CRITIC. *J. Supercomput.* **2024**, *80*, 16133–16172. [CrossRef]
8. Liang, L.; Peng, H.; Li, G.Y.; Shen, X. Vehicular Communications: A Physical Layer Perspective. *IEEE Trans. Veh. Technol.* **2017**, *66*, 10647–10659. [CrossRef]
9. Saini, M.; Alelaiwi, A.; Saddik, A.E. How Close Are We to Realizing a Pragmatic VANET Solution? A Meta-Survey. *ACM Comput. Surv.* **2015**, *48*, 1–40. [CrossRef]
10. Dhiman, A.; Kumar, R. A Comparative Study of Position-Based Routing Protocols in VANETs. In Proceedings of the International Conference on Intelligent and Sustainable Systems (ICISS), Palladam, India, 21–22 February 2019; pp. 306–311.
11. Ullah, A.; Yao, X.; Shaheen, S.; Ning, H. Advances in Position-Based Routing Towards ITS Enabled FoG-Oriented VANET—A Survey. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 828–840. [CrossRef]
12. Nardini, G.; Sabella, D.; Stea, G.; Thakkar, P.; Virdis, A. Simu5G: An OMNeT++ Library for End-to-End Performance Evaluation of 5G Networks. *IEEE Access* **2020**, *8*, 181176–181191. [CrossRef]
13. Patsakis, C.; Dellios, K.; Bouroche, M. Towards a Distributed Secure In-Vehicle Communication Architecture for Modern Vehicles. *Comput. Secur.* **2014**, *40*, 60–74. [CrossRef]
14. Cao, Y.; Wang, T.; Kaiwartya, O.; Min, G.; Ahmad, N.; Abdullah, A.H. An EV Charging Management System Concerning Drivers' Trip Duration and Mobility Uncertainty. *IEEE Trans. Syst. Man Cybern. Syst.* **2018**, *48*, 596–607. [CrossRef]

15. Ye, H.; Liang, L.; Ye, G.J.; Li, K.; Kim, L.; Lu, L.; Wu, M. Machine Learning for Vehicular Networks: Recent Advances and Application Examples. *IEEE Veh. Technol. Mag.* **2018**, *13*, 94–101. [CrossRef]
16. Alpaydin, E. *Introduction to Machine Learning*; MIT Press: Cambridge, MA, USA, 2014.
17. Schmidhuber, J. Deep Learning in Neural Networks: An Overview. *Neural Netw.* **2015**, *61*, 85–117. [PubMed]
18. Bartoletti, S.; Masini, B.M.; Martinez, V.; Sarris, I.; Bazzi, A. Impact of the Generation Interval on the Performance of Side-Link C-V2X Autonomous Mode. *IEEE Access* **2021**, *9*, 35121–35135. [CrossRef]
19. *IEEE Standard P1609.0/D9*; IEEE Draft Guide for Wireless Access in Vehicular Environments (WAVE)—Architecture. IEEE: Piscataway, NJ, USA, 2017; pp. 1–104.
20. Li, J.; Shi, M.; Li, J.; Yao, D. Media Access Process Modeling of LTEV-Direct Communication Based on Markov Chain. In Proceedings of the IEEE Intelligent Vehicles Symposium (IV), Changshu, China, 26–30 June 2018; pp. 61–66.
21. Chen, S.; Hu, J.; Shi, Y.; Zhao, L. LTE-V: A TD-LTE-Based V2X Solution for Future Vehicular Network. *IEEE Internet Things J.* **2016**, *3*, 997–1005. [CrossRef]
22. Gupta, S.K.; Khan, J.Y.; Ngo, D.T. *An LTE-Direct-Based Communication System for Safety Services in Vehicular Networks*; InTechOpen: London, UK, 2020.
23. Christopoulou, M.; Barmpounakis, S.; Koumaras, H.; Kaloxylos, A. Artificial Intelligence and Machine Learning as Key Enablers for V2X Communications: A Comprehensive Survey. *Veh. Commun.* **2023**, *39*, 100569. [CrossRef]
24. Daniel, A.; Paul, A.; Ahmad, A.; Rho, S. Cooperative Intelligence of Vehicles for Intelligent Transportation Systems (ITS). *Wirel. Pers. Commun.* **2016**, *87*, 461–484. [CrossRef]
25. Azhdari, M.S.; Barati, A.; Barati, H. A Cluster-Based Routing Method with Authentication Capability in Vehicular Ad Hoc Networks (VANETs). *J. Parallel Distrib. Comput.* **2022**, *169*, 1–23. [CrossRef]
26. Amin, R.; Rojas, E.; Aqdus, A.; Ramzan, S.; Casillas-Perez, D.; Arco, J.M. A Survey on Machine Learning Techniques for Routing Optimization in SDN. *IEEE Access* **2021**, *9*, 104582. [CrossRef]
27. Yazici, I.; Shayea, I.; Din, J. A Survey of Applications of Artificial Intelligence and Machine Learning in Future Mobile Networks-Enabled Systems. *Eng. Sci. Technol. Int. J.* **2023**, *44*, 101455. [CrossRef]
28. Badillo, S.; Banfai, B.; Birzele, F.; Davydov, I.I.; Hutchinson, L.; Kam-Thong, T.; Zhang, J.D. An Introduction to Machine Learning. *Clin. Pharmacol. Ther.* **2020**, *107*, 871–885. [CrossRef]
29. Akbari, M.R.; Barati, H.; Barati, A. An Overlapping Routing Approach for Sending Data from Things to the Cloud Inspired by Fog Technology in the Large-Scale IoT Ecosystem. *Wirel. Netw.* **2022**, *28*, 521–538. [CrossRef]
30. Zantalis, F.; Koulouras, G.; Karabetsos, S.; Kandris, D. A Review of Machine Learning and IoT in Smart Transportation. *Future Internet* **2019**, *11*, 94. [CrossRef]
31. Sirohi, D.; Kumar, N.; Rana, P.S. Convolutional Neural Networks for 5G-Enabled Intelligent Transportation System: A Systematic Review. *Comput. Commun.* **2020**, *153*, 459–498. [CrossRef]
32. Ullah, Z.; Al-Turjman, F.; Mostarda, L.; Gagliardi, R. Applications of Artificial Intelligence and Machine Learning in Smart Cities. *Comput. Commun.* **2020**, *154*, 313–323. [CrossRef]
33. Hossain, M.A.; Noor, R.M.; Yau, K.A.; Azzuhri, S.R.; Z'aba, M.R.; Ahmedy, I.A. Comprehensive Survey of Machine Learning Approaches in Cognitive Radio-Based Vehicular Ad Hoc Networks. *IEEE Access* **2020**, *8*, 78054. [CrossRef]
34. Ali, S.S.; Choi, B.J. State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review. *Electronics* **2020**, *9*, 1030. [CrossRef]
35. Rekkas, V.P.; Sotiroudis, S.; Sarigiannidis, P.; Wan, S.; Karagiannidis, G.K.; Goudos, S.K. Machine Learning in Beyond 5G/6G Networks—State-of-the-Art and Future Trends. *Electronics* **2021**, *10*, 2786. [CrossRef]
36. Dogra, A.K.; Kaur, J. Moving Towards Smart Transportation with Machine Learning and Internet of Things (IoT): A Review. *J. Smart Environ. Green Comput.* **2022**, *2*, 3–18. [CrossRef]
37. Hurbean, L.; Danaiata, D.; Militaru, F.; Dodea, A.-M.; Negovan, A.-M. Open Data Based Machine Learning Applications in Smart Cities: A Systematic Literature Review. *Electronics* **2021**, *10*, 2997. [CrossRef]
38. Sharma, H.; Haque, A.; Blaabjerg, F. Machine Learning in Wireless Sensor Networks for Smart Cities: A Survey. *Electronics* **2021**, *10*, 1012. [CrossRef]
39. Kumbhar, A.; Dhawale, P.G.; Kumbhar, S.; Patil, U.; Magdum, P. A Comprehensive Review: Machine Learning and Its Application in Integrated Power Systems. *Energy Rep.* **2021**, *7*, 5467–5474. [CrossRef]
40. Farhoumandi, M.; Zhou, Q.; Shahidehpour, M. A Review of Machine Learning Applications in IoT-Integrated Modern Power Systems. *Electr. J.* **2021**, *34*, 106879. [CrossRef]
41. Talpur, A.; Gurusamy, M. Machine Learning for Security in Vehicular Networks: A Comprehensive Survey. *IEEE Commun. Surv. Tutorials* **2021**, *24*, 346–379. [CrossRef]
42. Chatterjee, T.; Karmakar, R.; Kaddoum, G.; Chattopadhyay, S.; Chakraborty, S. A Survey of VANET/V2X Routing from the Perspective of Non-Learning- and Learning-Based Approaches. *IEEE Access* **2022**, *10*, 23022–23050. [CrossRef]

43. Mchergui, A.; Moulahi, T.; Zeadally, S. Survey on Artificial Intelligence (AI) Techniques for Vehicular Ad-Hoc Networks (VANETs). *Veh. Commun.* **2022**, *34*, 100403. [CrossRef]
44. Haddaji, A.; Ayed, S.; Fourati, L.C. Artificial Intelligence Techniques to Mitigate Cyber-Attacks within Vehicular Networks: Survey. *Comput. Electr. Eng.* **2022**, *104*, 108460. [CrossRef]
45. Idrisa, M.Y.I.; Ahmedya, I.; Soona, T.K.; Yahuza, M.; Tambuwald, A.B.; Alie, U. Cognitive Radio and Machine Learning Modalities for Enhancing the Smart Transportation System: A Systematic Literature Review. *ICT Express* **2024**, *10*, 693–734. [CrossRef]
46. Gandhi, J.; Narmawala, Z. A Comprehensive Survey on Machine Learning Techniques in Opportunistic Networks: Advances, Challenges and Future Directions. *Pervasive Mob. Comput.* **2024**, *100*, 101917. [CrossRef]
47. Balta, M.; Özçelik, I. A 3-Stage Fuzzy-Decision Tree Model for Traffic Signal Optimization in Urban City via a SDN-Based VANET Architecture. *Future Gener. Comput. Syst.* **2020**, *104*, 142–158. [CrossRef]
48. Kumbhar, F.H.; Shin, S.Y. DT-VAR: Decision Tree Predicted Compatibility Based Vehicular Ad-Hoc Reliable Routing. *IEEE Wireless Commun. Lett.* **2020**, *10*, 87–91. [CrossRef]
49. Ghaleb, F.A.; Saeed, F.; Al-Sarem, M.; Al-Rimy, B.A.S.; Boulila, W.; Eljialy, A.E.M.; Aloufi, K.; Alazab, M. Misbehavior-Aware On-Demand Collaborative Intrusion Detection System Using Distributed Ensemble Learning for VANET. *Electronics* **2020**, *9*, 1411. [CrossRef]
50. Zhou, Y.; Xu, X.; Liu, C.; Li, Y. Optimization Method of MAC Protocol Based on SVM Neural Network in VANET. *Int. J. Internet Protoc. Technol.* **2020**, *13*, 158–166. [CrossRef]
51. Sangare, M.; Banerjee, S.; Muhlethaler, P.; Bouzefrane, S. Predicting Transmission Success with Support Vector Machine in VANETs. In Proceedings of the 2018 IFIP/IEEE International Conference on Performance Evaluation and Modeling in Wired and Wireless Networks (PEMWN), Toulouse, France, 26–28 September 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
52. Liu, T.; Shi, S.; Gu, X. Naive Bayes Classifier Based Driving Habit Prediction Scheme for VANET Stable Clustering. *Mob. Netw. Appl.* **2020**, *25*, 1708–1714. [CrossRef]
53. Guo, X.; Chen, Y.; Cao, L.; Zhang, D.; Jiang, Y. A Receiver-Forwarding Decision Scheme Based on Bayesian for NDN-VANET. *China Commun.* **2020**, *17*, 106–120. [CrossRef]
54. Cheng, S.; Lu, F.; Peng, P.; Wu, S. Short-Term Traffic Forecasting: An Adaptive STKNN Model that Considers Spatial Heterogeneity. *Comput. Environ. Urban Syst.* **2018**, *71*, 186–198. [CrossRef]
55. Luo, X.; Li, D.; Yang, Y.; Zhang, S. Spatiotemporal Traffic Flow Prediction with KNN and LSTM. *J. Adv. Transp.* **2019**, *2019*, 4145353. [CrossRef]
56. Naja, R. Random Forest Learning for Performance Improvement in Vehicular Networks: VLC Platooning Study Case. Doctoral Dissertation, Lebanese University, Beirut, Lebanon, 2020.
57. Dogru, N.; Subasi, A. Traffic Accident Detection Using Random Forest Classifier. In Proceedings of the 2018 15th Learning and Technology Conference (L&T), Jeddah, Saudi Arabia, 25–26 February 2018; IEEE: Piscataway, NJ, USA; pp. 40–45.
58. Islam, R.; Shahjalal, M.A. Late Breaking Results: Predicting DRC Violations Using Ensemble Random Forest Algorithm. In Proceedings of the 56th Annual Design Automation Conference 2019, New York, NY, USA, 2–6 June 2019; pp. 1–2.
59. Yuan, G.-X.; Ho, C.-H.; Lin, C.-J. Recent Advances of Large-Scale Linear Classification. *Proc. IEEE* **2012**, *100*, 2584–2603. [CrossRef]
60. Dong, X.; Yu, Z.; Cao, W.; Shi, Y.; Ma, Q. A Survey on Ensemble Learning. *Front. Comput. Sci.* **2020**, *14*, 241–258. [CrossRef]
61. Saouda, B.; Shayeab, I.; Yahyac, A.E.; Shamsand, Z.A.; Alhammadie, A.; Alawadd, M.A.; Alkhrijahd, Y. Artificial Intelligence, Internet of Things, and 6G Methodologies in the Context of Vehicular Ad-hoc Networks (VANETs): Survey. *ICT Express* **2024**, *10*, 959–980. [CrossRef]
62. Venkata, P.; Meyyappan, S.; RamakoteswaraRao, A. Maximum Power Point Tracking with Regression Machine Learning Algorithms for Solar PV Systems. *Int. J. Renew. Energy Res.* **2022**, *12*, 1327–1338.
63. Maabreh, M.; Almasabha, G. Machine Learning Regression Algorithms for Shear Strength Prediction of SFRC-DBs: Performance Evaluation and Comparisons. *Arab. J. Sci. Eng.* **2024**, *49*, 4711–4727. [CrossRef]
64. Szeto, W.Y.; Wong, R.C.P.; Yang, W.H. Guiding Vacant Taxi Drivers to Demand Locations by Taxi-Calling Signals: A Sequential Binary Logistic Regression Modeling Approach and Policy Implications. *Transp. Policy* **2019**, *76*, 100–110. [CrossRef]
65. Bansal, S.K.; Bisen, A.S.; Gupta, R. A Secure Hashing Technique for K-Means Based Cluster Approach in VANET. In Proceedings of the 2016 International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES), Paralakhemundi, India, 3–5 October 2016; IEEE: Piscataway, NJ, USA; pp. 2037–2041.
66. Kandali, K.; Bennis, L.; Halaq, H.; Bennis, H. A Novel K-Means Powered Algorithm for Efficient Clustering in Vehicular Ad-Hoc Networks. *Int. J. Electr. Comput. Eng.* **2023**, *13*, 3140–3148. [CrossRef]
67. Khatri, N.; Lee, S.; Mateen, A.; Nam, S.Y. Event Message Clustering Algorithm for Selection of Majority Message in VANETs. *IEEE Access* **2023**, *11*, 14621–14635. [CrossRef]
68. Patel, S.; Sihmar, S.; Jatain, A. A Study of Hierarchical Clustering Algorithms. In Proceedings of the 2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 11–13 March 2015; pp. 537–541.
69. Reynolds, D. *Gaussian Mixture Models*; Springer: Boston, MA, USA, 2009; pp. 659–663.

70. Khan, T.I.; Sakib, N.; Hassan, M.M.; Ide, S. Gaussian Mixture Model in Clustering Acoustic Emission Signals for Characterizing Osteoarthritic Knees. *Biomed. Signal Process. Control.* **2024**, *87*, 105510. [CrossRef]
71. Smith, S.P. Exploring Cybersickness Experiences via a Markov Chain Model. *IEEE Access* **2024**, *12*, 33595–33604. [CrossRef]
72. Saize, S.; Yang, X. On the Definitions of Hidden Markov Models. *Appl. Math. Model.* **2024**, *125*, 617–629. [CrossRef]
73. Zhao, H.; Mao, T.; Yu, H.; Zhang, M.K.; Zhu, H. A Driving Risk Prediction Algorithm Based on PCA-BP Neural Network. In Proceedings of the Vehicular Communication, 2018 10th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Hangzhou, China, 25–26 August 2018; IEEE: Piscataway, NJ, USA, 2018; Volume 2, pp. 164–169.
74. Khodaei, M.; Papadimitratos, P. Security & Privacy for Vehicular Communication Systems. Available online: https://people.kth.se/~khodaei/files/posters/cysep17-KeyITS.pdf (accessed on 17 December 2024).
75. Malik, A.; Pandey, B.; Wu, C.-C. Secure Model to Generate Path Map for Vehicles in Unusual Road Incidents Using Association Rule Based Mining in VANET. *J. Electron. Sci. Technol.* **2018**, *16*, 153–162.
76. Sutton, R.S.; Barto, A.G. *Reinforcement Learning: An Introduction*; MIT Press: Cambridge, MA, USA, 2018.
77. Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A.A.; Veness, J.; Bellemare, M.G.; Graves, A.; Riedmiller, M.; Fidjeland, A.K.; Ostrovski, G.; et al. Human-Level Control through Deep Reinforcement Learning. *Nature* **2015**, *518*, 529–533. [CrossRef] [PubMed]
78. Hessel, M.; Modayil, J.; van Hasselt, H.; Schaul, T.; Ostrovski, G.; Dabney, W.; Horgan, D.; Piot, B.; Azar, M.; Silver, D. Rainbow: Combining Improvements in Deep Reinforcement Learning. *arXiv* **2017**, arXiv:1710.02298. [CrossRef]
79. Dai, C.; Xiao, X.; Xiao, L.; Cheng, P. Reinforcement Learning Based Power Control for VANET Broadcast Against Jamming. In Proceedings of the 2018 IEEE Global Communications Conference (GLOBECOM), Abu Dhabi, United Arab Emirates, 9–13 December 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
80. Wu, J.; Fang, M.; Li, H.; Li, X. RSU-Assisted Traffic-Aware Routing Based on Reinforcement Learning for Urban VANETs. *IEEE Access* **2020**, *8*, 5733–5748. [CrossRef]
81. Schulz, V.H. Reinforcement Learning: An Introduction—A Review. *SIAM Rev.* **2021**, *63*, 423.
82. Jang, B.; Kim, M.; Harerimana, G.; Kim, J.W. Q-Learning Algorithms: A Comprehensive Classification and Applications. *IEEE Access* **2019**, *7*, 133653–133667. [CrossRef]
83. Hasselt, H.V. Double Q-Learning. In Proceedings of the Advances in Neural Information Processing Systems, Vancouver, BC, Canada, 6–9 December 2010; pp. 2613–2621.
84. Mnih, V.; Kavukcuoglu, K.; Silver, D.; Graves, A.; Antonoglou, I.; Wierstra, D.; Riedmiller, M. Playing Atari with Deep Reinforcement Learning. *arXiv* **2013**, arXiv:1312.5602.
85. Lalwani, P.; Ganeshan, R. A Novel CNN-BiLSTM-GRU Hybrid Deep Learning Model for Human Activity Recognition. *Int. J. Comput. Intell. Syst.* **2024**, *17*, 278. [CrossRef]
86. Oliver, A.; Odena, A.; Raffel, C.A.; Cubuk, E.D.; Goodfellow, I. Realistic Evaluation of Deep Semi-Supervised Learning Algorithms. *arXiv* **2019**, arXiv:1804.09170.
87. Orozco, M.C.E.; Rebong, C.B. Vehicular Detection and Classification for Intelligent Transportation System: A Deep Learning Approach Using Faster R-CNN Model. *Platero* **2019**, *180*, 36551. [CrossRef]
88. Chen, M.; Chen, J.; Chen, X.; Zhang, S.; Xu, S. A Deep Learning-Based Resource Allocation Scheme in Vehicular Communication Systems. In Proceedings of the 2019 IEEE Wireless Communications and Networking Conference (WCNC), Manchester, UK, 26 October–2 November 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–6.
89. Bahra, N.; Pierre, S. RNN-Based User Trajectory Prediction Using a Preprocessed Dataset. In Proceedings of the 2020 16th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob 50308), Thessaloniki, Greece, 12–14 October 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–6.
90. Cho, K.; van Merrienboer, B.; Gulcehre, C.; Bahdanau, D.; Bougares, F.; Schwenk, H.; Bengio, Y. Learning Phrase Representations Using RNN Encoder-Decoder for Statistical Machine Translation. *arXiv* **2014**, arXiv:1406.1078.
91. Yu, J.J.Q.; Gu, J. Real-Time Traffic Speed Estimation with Graph Convolutional Generative Autoencoder. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 3940–3951. [CrossRef]
92. Moussavi-Khalkhali, A.; Jamshidi, M. Feature Fusion Models for Deep Autoencoders: Application to Traffic Flow Prediction. *Appl. Artif. Intell.* **2019**, *33*, 1179–1198. [CrossRef]
93. Indira, K.; Ajitha, P.; Reshma, V.; Tamizhselvi, A. An Efficient Secured Routing Protocol for Software Defined Internet of Vehicles. In Proceedings of the 2019 International Conference on Computational Intelligence in Data Science (ICCIDS), Chennai, India, 21–23 February 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–4.
94. Chen, C.; Wang, H.; Yuan, F.; Jia, H.; Yao, B. Bus Travel Time Prediction Based on Deep Belief Network with Back-Propagation. *Neural Comput. Appl.* **2020**, *32*, 10435–10449. [CrossRef]
95. Sheng, W.H.Z.; Wang, Z. Vehicle Lane-Change Trajectory Prediction Model Based on Generative Adversarial Networks. *J. South China Univ. Technol. Nat. Sci.* **2020**, *48*, 32.

96. Sundareswaran, A.; Lavanya, K. Real-Time Vehicle Traffic Prediction in Apache Spark Using Ensemble Learning for Deep Neural Networks. *Int. J. Intell. Inf. Technol.* **2020**, *16*, 19–36. [CrossRef]
97. Xing, Y.; Lv, C.; Wang, H.; Cao, D.; Velenis, E. An Ensemble Deep Learning Approach for Driver Lane Change Intention Inference. *Transp. Res. Part C Emerg. Technol.* **2020**, *115*, 102615. [CrossRef]
98. Ha, C.B.; Song, H.K. Signal Detection Scheme Based on Adaptive Ensemble Deep Learning Model. *IEEE Access* **2018**, *6*, 21342–21349. [CrossRef]
99. Nazari, M.; Oroojlooy, A.; Snyder, L.V.; Takác, M. Reinforcement Learning for Solving the Vehicle Routing Problem. *arXiv* **2018**, arXiv:1802.04240.
100. Liang, X.; Du, X.; Wang, G.; Han, Z. Deep Reinforcement Learning for Traffic Light Control in Vehicular Networks. *arXiv* **2018**, arXiv:1803.11115.
101. Ning, Z.; Dong, P.; Wang, X.; Obaidat, M.S.; Hu, X.; Guo, L.; Guo, Y.; Huang, J.; Hu, B. When Deep Reinforcement Learning Meets 5G-Enabled Vehicular Networks: A Distributed Offloading Framework for Traffic Big Data. *IEEE Trans. Ind. Inform.* **2019**, *16*, 1352–1361. [CrossRef]
102. Sultana, R.; Grover, J.; Tripathi, M. Intelligent Defense Strategies: Comprehensive Attack Detection in VANET with Deep Reinforcement Learning. *Pervasive Mob. Comput.* **2024**, *103*, 101962. [CrossRef]
103. Le, T.-D.; Kaddoum, G. LSTM-Based Channel Access Scheme for Vehicles in Cognitive Vehicular Networks with Multi-Agent Settings. *IEEE Trans. Veh. Technol.* **2021**, *70*, 9132–9143. [CrossRef]
104. Ashraf, J.; Bakhshi, A.D.; Moustafa, N.; Khurshid, H.; Javed, A.; Beheshti, A. Novel Deep Learning-Enabled LSTM Autoencoder Architecture for Discovering Anomalous Events from Intelligent Transportation Systems. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 4507–4518. [CrossRef]
105. Bibi, R.; Saeed, Y.; Zeb, A.; Ghazal, T.M.; Rahman, T.; Said, R.A.; Abbas, S.; Ahmad, M.; Khan, M.A. Edge AI-Based Automated Detection and Classification of Road Anomalies in VANET Using Deep Learning. *Comput. Intell. Neurosci.* **2021**, *2021*, 6262194. [CrossRef]
106. Bitam, S.; Mellouk, A.; Zeadally, S. Bio-Inspired Routing Algorithms Survey for Vehicular Ad-Hoc Networks. *IEEE Commun. Surv. Tutor.* **2015**, *17*, 843–867. [CrossRef]
107. Aadil, F.; Bajwa, K.B.; Khan, S.; Chaudary, N.M.; Akram, A. CACONET: Ant Colony Optimization (ACO) Based Clustering Algorithm for VANET. *PLoS ONE* **2016**, *11*, e0154080. [CrossRef] [PubMed]
108. Suganya, E.; Rajan, C. An AdaBoost-Modified Classifier Using Particle Swarm Optimization and Stochastic Diffusion Search in Wireless IoT Networks. *Wirel. Netw.* **2020**, *27*, 2287–2299. [CrossRef]
109. Krundyshev, V.; Kalinin, M.; Zegzhda, P. Artificial Swarm Algorithm for VANET Protection Against Routing Attacks. In Proceedings of the 2018 IEEE Industrial Cyber-Physical Systems (ICPS), St. Petersburg, Russia, 15–18 May 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 795–800.
110. Poonia, R.C. A Performance Evaluation of Routing Protocols for Vehicular Ad Hoc Networks with Swarm Intelligence. *Int. J. Syst. Assur. Eng. Manag.* **2018**, *9*, 830–835. [CrossRef]
111. Desai, D.; El-Ocla, H.; Purohit, S. Data Dissemination in VANETs Using Particle Swarm Optimization. *Sensors* **2023**, *23*, 2124. [CrossRef]
112. Liu, J.; Weng, H.; Ge, Y.; Li, S.; Cui, X. A Self-Healing Routing Strategy Based on Ant Colony Optimization for Vehicular Ad Hoc Networks. *IEEE Internet Things J.* **2022**, *9*, 22695–22708. [CrossRef]
113. Mandjes, M.; Storm, J. A Diffusion-Based Analysis of a Multiclass Road Traffic Network. *Stoch. Syst.* **2021**, *11*, 60–81. [CrossRef]
114. Weber, J.S.; Neves, M.; Ferreto, T. VANET Simulators: An Updated Review. *J. Braz. Comput. Soc.* **2021**, *27*, 8. [CrossRef]
115. Aljabry, I.A.; Al-Suhail, G.A. A Survey on Network Simulators for Vehicular Adhoc Networks (VANETs). *Int. J. Comput. Appl.* **2021**, *174*, 1–9.
116. Gillani, M.; Niaz, H.A.; Farooq, M.U.; Ullah, A. Data Collection Protocols for VANETs: A Survey. *Complex Intell. Syst.* **2022**, *8*, 2593–2622. [CrossRef]
117. Al-Shareeda, M.A.; Manickam, S. A Systematic Literature Review on Security of Vehicular Ad-Hoc Network (VANET) Based on VEINS Framework. *IEEE Access* **2023**, *11*, 46218–46228. [CrossRef]
118. Shabir, B.; Khan, M.A.; Rahman, A.U.; Malik, A.W.; Wahid, A. Congestion Avoidance in Vehicular Networks: A Contemporary Survey. *IEEE Access* **2019**, *7*, 173196–173215. [CrossRef]
119. Chang, X. Network Simulations with OPNET. In Proceedings of the Winter Simulation Conference, Simulation—A Bridge to the Future, Phoenix, AZ, USA, 5–8 December 1999; ACM: New York, NY, USA, 1999; Volume 1, pp. 307–314.
120. Wang, S.-Y.; Chou, C.-L.; Yang, C.-M. EstiNet OpenFlow Network Simulator and Emulator. *IEEE Commun. Mag.* **2013**, *51*, 110–117. [CrossRef]
121. Karabulut, M.A.; Shah, A.S.; Ilhan, H.; Pathan, A.S.K.; Atiquzzaman, M. Inspecting VANET with Various Critical Aspects—A Systematic Review. *Ad Hoc Netw.* **2023**, *150*, 103281. [CrossRef]

122. Sommer, C.; German, R.; Dressler, F. Bidirectionally Coupled Network and Road Traffic Simulation for Improved IVC Analysis. *IEEE Trans. Mob. Comput.* **2011**, *10*, 3–15. [CrossRef]
123. Zarrad, A.; Alsmadi, I. Evaluating Network Test Scenarios for Network Simulators Systems. *Int. J. Distrib. Sens. Netw.* **2017**, *13*, 1550147717738216. [CrossRef]
124. Protzmann, R.; Schünemann, B.; Radusch, I. Simulation of Convergent Networks for Intelligent Transport Systems with VSimRTI. In *Networking Simulation for Intelligent Transportation Systems: High Mobile Wireless Nodes*; Wiley: Hoboken, NJ, USA, 2017; pp. 1–28.
125. Hassan, M.A.; Salem, H.; Bailek, N.; Kisi, O. Random Forest Ensemble-Based Predictions of On-Road Vehicular Emissions and Fuel Consumption in Developing Urban Areas. *Sustainability* **2023**, *15*, 1503. [CrossRef]
126. Zhao, H.; Cheng, H.; Mao, T.; He, C. Research on Traffic Accident Prediction Model Based on Convolutional Neural Networks in VANET. In Proceedings of the 2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD), Chengdu, China, 25–28 May 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 79–84.
127. Samara, G. Lane Prediction Optimization in VANET. *Egypt. Inform. J.* **2020**, *22*, 411–416. [CrossRef]
128. Soon, F.C.; Khaw, H.Y.; Chuah, J.H.; Kanesan, J. Semi-Supervised PCA Convolutional Network for Vehicle Type Classification. *IEEE Trans. Veh. Technol.* **2020**, *69*, 8267–8277. [CrossRef]
129. Wang, G.; Kim, J. The Prediction of Traffic Congestion and Incident on Urban Road Networks Using Naive Bayes Classifier. In Proceedings of the 38th Australasian Transport Research Forum (ATRF), Melbourne, Australia, 16–18 November 2016.
130. Bhatia, J.; Dave, R.; Bhayani, H.; Tanwar, S.; Nayyar, A. SDN-Based Real-Time Urban Traffic Analysis in VANET Environment. *Comput. Commun.* **2020**, *149*, 162–175. [CrossRef]
131. Tao, Y.; Sun, P.; Boukerche, A. A Novel Travel-Delay Aware Short-Term Vehicular Traffic Flow Prediction Scheme for VANET. In Proceedings of the 2019 IEEE Wireless Communications and Networking Conference (WCNC), Marrakesh, Morocco, 15–18 April 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–6.
132. Sun, P.; Boukerche, A.; Tao, Y. SSGRU: A Novel Hybrid Stacked GRU-Based Traffic Volume Prediction Approach in a Road Network. *Comput. Commun.* **2020**, *160*, 502–511. [CrossRef]
133. Zhang, W.; Yu, Y.; Qi, Y.; Shu, F.; Wang, Y. Short-Term Traffic Flow Prediction Based on Spatio-Temporal Analysis and CNN Deep Learning. *Transp. A Transp. Sci.* **2019**, *15*, 1688–1711. [CrossRef]
134. Khoza, E.; Tu, C.; Owolawi, P.A. Decreasing Traffic Congestion in VANETs Using an Improved Hybrid Ant Colony Optimization Algorithm. *J. Commun.* **2020**, *15*, 676–686. [CrossRef]
135. Jadaan, K.S.; Al-Fayyad, M.; Gammoh, H.F. Prediction of Road Traffic Accidents in Jordan Using Artificial Neural Network (ANN). *J. Traffic Logist. Eng.* **2014**, *2*, 92–94. [CrossRef]
136. Rasyidi, M.A.; Kim, J.; Ryu, K.R. Short-Term Prediction of Vehicle Speed on Main City Roads Using the K-Nearest Neighbor Algorithm. *J. Intell. Inf. Syst.* **2014**, *20*, 121–131. [CrossRef]
137. Moussaoui, B.; Djahel, S.; Smati, M.; Murphy, J. A Cross-Layer Approach for Efficient Multimedia Data Dissemination in VANETs. *Veh. Commun.* **2017**, *9*, 127–134. [CrossRef]
138. Contreras-Castillo, J.; Zeadally, S.; Guerrero-Ibañez, J.A. Internet of Vehicles: Architecture, Protocols, and Security. *IEEE Int. Things J.* **2017**, *5*, 3701–3709. [CrossRef]
139. Guerrero-Ibanez, J.A.; Zeadally, S.; Contreras-Castillo, J. Integration Challenges of Intelligent Transportation Systems with Connected Vehicle, Cloud Computing, and Internet of Things Technologies. *IEEE Wirel. Commun.* **2015**, *22*, 122–128. [CrossRef]
140. Reshma, S.; Chetanaprakash, C. Advancement in Infotainment System in Automotive Sector with Vehicular Cloud Network and Current State of Art. *Int. J. Electr. Comput. Eng.* **2020**, *10*, 2077.
141. Guo, J.; Song, B.; Yu, F.R.; Chi, Y.; Yuen, C. Fast Video Frame Correlation Analysis for Vehicular Networks by Using CVS–CNN. *IEEE Trans. Veh. Technol.* **2019**, *68*, 6286–6292. [CrossRef]
142. Khamparia, A.; Saini, G.; Pandey, B.; Tiwari, S.; Gupta, D.; Khanna, A. KDSAE: Chronic Kidney Disease Classification with Multimedia Data Learning Using Deep Stacked Autoencoder Network. *Multimed. Tools Appl.* **2019**, *79*, 35425–35440. [CrossRef]
143. Yang, Q.; Jiang, T.; Li, W.; Liu, G.; Rawat, D.B.; Wu, J. Multimedia and Social Data Processing in Vehicular Networks. *Mob. Netw. Appl.* **2019**, *25*, 620–622. [CrossRef]
144. Manivannan, D.; Moni, S.S.; Zeadally, S. Secure Authentication and Privacy-Preserving Techniques in Vehicular Ad-Hoc Networks (VANETs). *Veh. Commun.* **2020**, *25*, 100247. [CrossRef]
145. Hussain, R.; Hussain, F.; Zeadally, S. Integration of VANET and 5G Security: A Review of Design and Implementation Issues. *Future Gener. Comput. Syst.* **2019**, *101*, 843–864. [CrossRef]
146. Arif, M.; Wang, G.; Bhuiyan, M.Z.A.; Wang, T.; Chen, J. A Survey on Security Attacks in VANETs: Communication, Applications, and Challenges. *Veh. Commun.* **2019**, *19*, 100179. [CrossRef]
147. Manickam, P.; Shankar, K.; Perumal, E.; Ilayaraja, M.; Kumar, K.S. Secure Data Transmission Through Reliable Vehicles in VANET Using Optimal Lightweight Cryptography. In *Cybersecurity and Secure Information Systems*; Springer: Cham, Switzerland, 2019; pp. 193–204.

148. Shah, S.; Ahmed, E.; Imran, M.; Zeadally, S. 5G for Vehicular Communications. *IEEE Commun. Mag.* **2018**, *56*, 111–117. [CrossRef]
149. Rehman, A.; Rehman, S.U.; Khan, M.; Alazab, M.; Reddy, T. CANintelliIDS: Detecting In-Vehicle Intrusion Attacks on a Controller Area Network Using CNN and Attention-Based GRU. *IEEE Trans. Netw. Sci. Eng.* **2021**, *8*, 1456–1466.
150. Otoum, S.; Kantarci, B.; Mouftah, H. Empowering Reinforcement Learning on Big Sensed Data for Intrusion Detection. In Proceedings of the ICC 2019—IEEE International Conference on Communications (ICC), Shanghai, China, 20–24 May 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–7.
151. Ghaleb, F.A.; Zainal, A.; Rassam, M.A.; Mohammed, F. An Effective Misbehavior Detection Model Using Artificial Neural Network for Vehicular Ad Hoc Network Applications. In Proceedings of the 2017 IEEE Conference on Application, Information and Network Security (AINS), Miri, Malaysia, 13–14 November 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 13–18.
152. Hasrouny, H.; Samhat, A.E.; Bassil, C.; Laouiti, A. Trust Model for Secure Group Leader-Based Communications in VANET. *Wirel. Netw.* **2019**, *25*, 4639–4661. [CrossRef]
153. Zeng, Y.; Qiu, M.; Zhu, D.; Xue, Z.; Xiong, J.; Liu, M. DeepVCM: A Deep Learning-Based Intrusion Detection Method in VANET. In Proceedings of the 2019 IEEE 5th International Conference on Big Data Security on Cloud (BigDataSecurity), IEEE International Conference on High Performance and Smart Computing (HPSC) and IEEE International Conference on Intelligent Data and Security (IDS), Washington, DC, USA, 27–29 May 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 288–293.
154. Shams, E.A.; Rizaner, A.; Ulusoy, A.H. Trust-Aware Support Vector Machine Intrusion Detection and Prevention System in Vehicular Ad Hoc Networks. *Comput. Secur.* **2018**, *78*, 245–254. [CrossRef]
155. Zhang, D.; Yu, F.R.; Yang, R.; Zhu, L. Software-Defined Vehicular Networks with Trust Management: A Deep Reinforcement Learning Approach. *IEEE Trans. Intell. Transp. Syst.* **2020**, *23*, 1400–1414. [CrossRef]
156. Alrehan, A.M.; Alhaidari, F.A. Machine Learning Techniques to Detect DDoS Attacks on VANET System: A Survey. In Proceedings of the 2019 on Computer Applications & Information Security (ICCAIS), Riyadh, Saudi Arabia, 1–3 May 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–6.
157. Elhoseny, M.; Shankar, K. Energy Efficient Optimal Routing for Communication in VANETs via Clustering Model. In *Emerging Technologies for Connected Internet of Vehicles and Intelligent Transportation System Networks*; Springer: Cham, Switzerland, 2020; pp. 1–14.
158. Miri, S.T.; Tabatabaei, S. Improved Routing in Vehicular Ad-Hoc Networks (VANETs) Based on Mobility and Bandwidth Available Criteria Using Fuzzy Logic. *Wirel. Pers. Commun.* **2020**, *113*, 1263–1278. [CrossRef]
159. Srinidhi, N.N.; Sagar, C.S.; Shreyas, J.; Dilip Kumar, S.M. An Improved PRoPHET-Random Forest Based Optimized Multi-Copy Routing for Opportunistic IoT Networks. *Internet Things* **2020**, *11*, 100203.
160. Nadarajan, J.; Kaliyaperumal, J. QoS-Aware and Secured Routing Algorithm Using Machine Intelligence in Next-Generation VANET. *Int. J. Syst. Assur. Eng. Manag.* **2021**, 1–12. [CrossRef]
161. Sun, Y.; Ravi, S.N.; Singh, V. Adaptive Activation Thresholding: Dynamic Routing Type Behavior for Interpretability in Convolutional Neural Networks. In Proceedings of the IEEE International Conference on Computer Vision, Seoul, Republic of Korea, 27 October–2 November 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 4938–4947.
162. Azzoug, Y.; Boukra, A. Bio-Inspired VANET Routing Optimization: An Overview. *Artif. Intell. Rev.* **2020**, *54*, 1005–1062. [CrossRef]
163. Noor-A-Rahim, M.; Liu, Z.; Lee, H.; Ali, G.M.N.; Pesch, D.; Xiao, P. A Survey on Resource Allocation in Vehicular Networks. *IEEE Trans. Intell. Transp. Syst.* **2020**, *23*, 701–721. [CrossRef]
164. Ashraf, M.I.; Liu, C.F.; Bennis, M.; Saad, W.; Hong, C.S. Dynamic Resource Allocation for Optimized Latency and Reliability in Vehicular Networks. *IEEE Access* **2018**, *6*, 63843–63858. [CrossRef]
165. Gansterer, M.; Hartl, R.F. Shared Resources in Collaborative Vehicle Routing. *TOP Off. J. Span. Soc. Stat. Oper. Res.* **2020**, *28*, 1–20. [CrossRef]
166. Liang, L.; Ye, H.; Li, G.Y. Spectrum Sharing in Vehicular Networks Based on Multi-Agent Reinforcement Learning. *IEEE J. Sel. Areas Commun.* **2019**, *37*, 2282–2292. [CrossRef]
167. Abidi, M.H.; Alkhalefah, H.; Moiduddin, K.; Alazab, M.; Mohammed, M.K.; Ameen, W.; Gadekallu, T.R. Optimal 5G Network Slicing Using Machine Learning and Deep Learning Concepts. *Comput. Stand. Interfaces* **2021**, *76*, 103518. [CrossRef]
168. Wu, Y.; Fang, X.; Wang, X. Mobility Management Through Scalable C/U-Plane Decoupling in IoV Networks. *IEEE Commun. Mag.* **2019**, *57*, 122–129. [CrossRef]
169. Skondras, E.; Michalas, A.; Vergados, D.D. Mobility Management on 5G Vehicular Cloud Computing Systems. *Veh. Commun.* **2019**, *16*, 15–44. [CrossRef]
170. Liu, W.; Shoji, Y. DeepVM: RNN-Based Vehicle Mobility Prediction to Support Intelligent Vehicle Applications. *IEEE Trans. Ind. Inform.* **2019**, *16*, 3997–4006. [CrossRef]
171. Bonanni, M.; Chiti, F.; Fantacci, R. Mobile Mist Computing for the Internet of Vehicles. *Internet Technol. Lett.* **2020**, *3*, e176. [CrossRef]
172. Mo, X.; Xing, Y.; Lv, C. Interaction-Aware Trajectory Prediction of Connected Vehicles Using CNN-LSTM Networks. *arXiv* **2020**, arXiv:2005.12134.

173. Boukerche, A.; Robson, E. Vehicular Cloud Computing: Architectures, Applications, and Mobility. *Comput. Netw.* **2018**, *135*, 171–189. [CrossRef]
174. Abdulshaheed, H.R.; Yaseen, Z.T.; Salman, A.M.; Al-Barazanchi, I. A Survey on the Use of WiMAX and Wi-Fi on Vehicular Ad-Hoc Networks (VANETs). *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *870*, 012122. [CrossRef]
175. Mchergui, A.; Moulahi, T.; Nasri, S. BaaS: Broadcast as a Service Cross-Layer Learning-Based Approach in Cloud-Assisted VANETs. *Comput. Netw.* **2020**, *182*, 107468. [CrossRef]
176. Yang, H.; Xiong, Z.; Zhao, J.; Niyato, D.; Yuen, C.; Deng, R. Deep Reinforcement Learning-Based Massive Access Management for Ultra-Reliable Low-Latency Communications. *IEEE Trans. Wirel. Commun.* **2020**, *20*, 2977–2990. [CrossRef]
177. Al-Joboury, I.M.; Al-Hemiary, E.H. Virtualized Network with Load Balancing for IoT-Based Fog-to-Cloud. *JOIV Int. J. Inform. Visual.* **2020**, *4*, 123–126. [CrossRef]
178. Wang, R. Intrusion Detection Technology of Internet of Vehicles Based on Deep Learning. In *Advances in Intelligent Systems and Computing: 2020 International Conference on Data Processing Techniques and Applications for Cyber-Physical Systems*; Springer: Singapore, 2020; Volume 1379.
179. Kelarestaghi, K.B.; Foruhandeh, M.; Heaslip, K.; Gerdes, R. Survey on Vehicular Ad Hoc Networks and Its Access Technologies Security Vulnerabilities and Countermeasures. *arXiv* **2019**, arXiv:1903.01541.
180. Zeadally, S.; Javed, M.A.; Hamida, E.B. Vehicular Communications for ITS: Standardization and Challenges. *IEEE Commun. Stand. Mag.* **2020**, *4*, 11–17. [CrossRef]
181. Zhao, X.; Zhang, X.; Li, Y. A Hierarchical Resource Allocation Scheme Based on Nash Bargaining Game in VANET. *Information* **2019**, *10*, 196. [CrossRef]
182. Chiti, F.; Fantacci, R.; Dei, E.; Han, Z. Context Aware Clustering in VANETs: A Game Theoretic Perspective. In Proceedings of the 2015 IEEE International Conference on Communications (ICC), London, UK, 8–12 June 2015. [CrossRef]
183. Kumari, A.; Kumar, S.; Raw, R.S. Modified Clustering and Incentivized Stable CH Selection for Reliable VANET Communication. *Cluster Comput.* **2024**, *27*, 11983–12005. [CrossRef]
184. Mukhtaruzzaman, M.; Atiquzzaman, M. Clustering in Vehicular Ad Hoc Network: Algorithms and Challenges. *Comput. Electr. Eng.* **2020**, *88*, 106851. [CrossRef]
185. Li, G.; Fang, S.; Ma, J.; Cheng, J. Modeling Merging Acceleration and Deceleration Behavior Based on Gradient-Boosting Decision Tree. *J. Transp. Eng. A Syst.* **2020**, *146*, 05020005. [CrossRef]
186. Pajila, P.B.; Sheena, B.G.; Gayathri, A.; Aswini, J.; Nalini, M. A Comprehensive Survey on Naïve Bayes Algorithm: Advantages, Limitations, and Applications. In Proceedings of the 2023 4th International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 20–22 September 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1228–1234.
187. Alsammak, I.L.H.; Sahib, H.M.A.; Itwee, W.H. An Enhanced Performance of K-Nearest Neighbor (K-NN) Classifier to Meet New Big Data Necessities. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *928*, 032013.
188. Mazziotta, M.; Pareto, A. Use and Misuse of PCA for Measuring Well-Being. *Soc. Indic. Res.* **2019**, *142*, 451–476. [CrossRef]
189. Bohra, N.; Bhatnagar, V. Tuning of CNN Architecture by CSA for EMNIST Data. In *Advances in Information Communication Technology and Computing: Proceedings of AICTC 2019*; Springer: Singapore, 2021; pp. 45–55.
190. Bohra, N.; Bhatnagar, V. Language Identification Using Stacked Convolutional Neural Network (SCNN). In Proceedings of the 11th International Conference on Cloud Computing, Data Science & Engineering, Noida, India, 28–29 January 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 20–25.
191. Chen, Q.; Wu, R. CNN Is All You Need. *arXiv* **2017**, arXiv:1712.09662.
192. Borji, A. Pros and Cons of GAN Evaluation Measures. *Comput. Vis. Image Underst.* **2019**, *179*, 41–65. [CrossRef]
193. Liang, D.; Krishnan, R.G.; Hoffman, M.D.; Jebara, T. Variational Autoencoders for Collaborative Filtering. In Proceedings of the 2018 World Wide Web Conference, Lyon, France, 23–27 April 2018; pp. 689–698.
194. Violanda, R.R.; Bernido, C.C. Modeling Vehicular Speed Fluctuations as a Stochastic Process with Exponentially Decaying Memory. *AIP Conf. Proc.* **2020**, *2286*, 030005.
195. Abbas, F.; Fan, P. Clustering-Based Reliable Low-Latency Routing Scheme Using ACO Method for Vehicular Networks. *Veh. Commun.* **2018**, *12*, 66–74. [CrossRef]
196. Sedighizadeh, D.; Mazaheripour, H. Optimization of Multi-Objective Vehicle Routing Problem Using a New Hybrid Algorithm Based on Particle Swarm Optimization and Artificial Bee Colony Algorithm Considering Precedence Constraints. *Alex. Eng. J.* **2018**, *57*, 2225–2239. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.