A Survey of Collaborative Machine Learning Using 5G Vehicular Communications

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***Abstract*—By enabling autonomous vehicles (AVs) to share data while driving, 5G vehicular communications allow AVs to collaborate on solving common autonomous driving tasks. AVs often rely on machine learning models to perform such tasks; as such, collaboration requires leveraging vehicular communications to improve the performance of machine learning algorithms. This paper provides a comprehensive literature survey of the intersection between machine learning for autonomous driving and vehicular communications. Throughout the paper, we explain how vehicle-to-vehicle (V2V) and vehicle-to-everything (V2X) communications are used to improve machine learning in AVs, answering five major questions regarding such systems. These questions include: 1) How can AVs effectively transmit data wirelessly on the road? 2) How do AVs manage the shared data? 3) How do AVs use shared data to improve their perception of the environment? 4) How do AVs use shared data to drive more safely and efficiently? and 5) How can AVs protect the privacy of shared data and prevent cyberattacks? We also summarize data sources that may support research in this area and discuss the future research potential surrounding these five questions.**

***Index Terms*—Vehicular communications, machine learning**

I. Introduction

As autonomous vehicles (AVs) enter the commercial market and advance towards full autonomy, more AVs will be present on the world's roadways [1]. Today, AVs rely on sensors including cameras and LiDAR to monitor the road in order to drive safely and efficiently [2]. However, if other AVs are also present on the road, the vehicles can send data between each other in a process called vehicle-to-vehicle (V2V) communication.

V2V communication allows AVs to share information in real-time, resulting in safer and more efficient driving [3]. For example, a pedestrian in a roadway might be occluded from view for one AV, but with V2V communication, another AV could communicate the pedestrian's location (Fig. 1), allowing them to be seen by all nearby vehicles. AVs can also communicate with other computers such as roadside units, which is referred to as vehicle-to-infrastructure (V2I) communication. The term vehicle-to-everything (V2X) encompasses both V2V and V2I paradigms.

As AVs become more ubiquitous, V2V and V2I communications can provide improvements to common autonomous driving tasks. They will also serve to connect AVs to the Internet of Things as a whole, allowing for an interconnected world (Fig. 2). 5G communication technologies are largely considered the future of V2V communications due to their high throughput, high bandwidth, and low latency, which are required for many aspects of autonomous driving [3].

Machine learning (ML) algorithms, especially deep neural networks, are currently the backbone of many cutting-edge

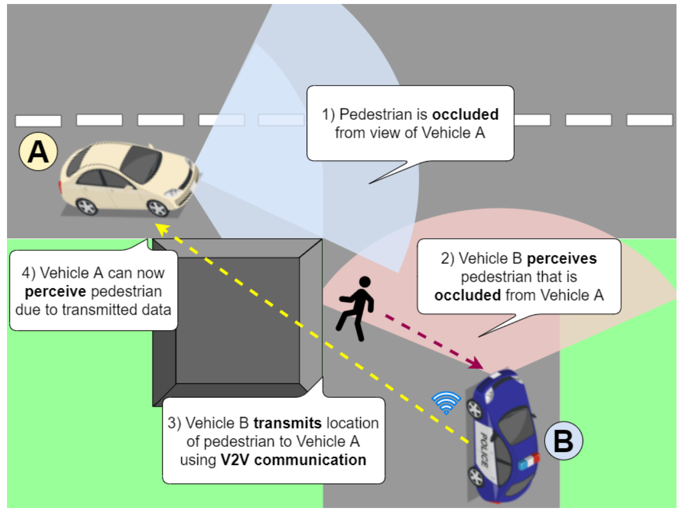

Fig. 1. Depiction of occlusion. The pedestrian is occluded from the top left vehicle by the building, but the lower right vehicle can detect the pedestrian and communicate this information to the top left car.

autonomous driving systems. In autonomous vehicles, deep neural networks are used for a variety of tasks, including object detection and semantic segmentation, vehicle control and collision avoidance, and optimal route planning [4]. However, these algorithms require informative data sources to perform accurately - data that can be provided by vehicular communications.

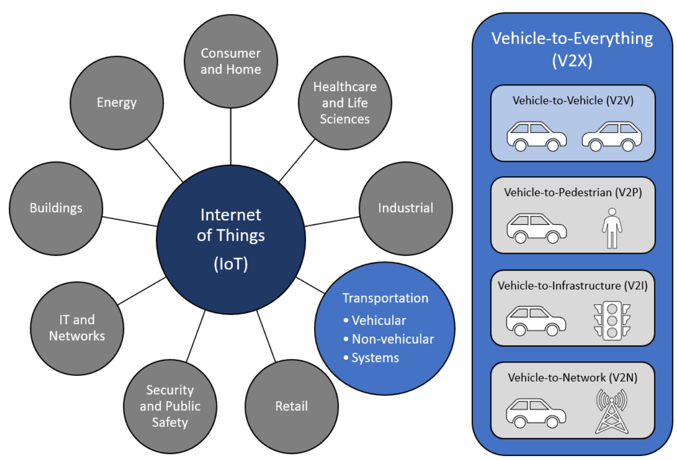

Fig. 2. Diagram of the IoT sectors and the relationship between V2V and V2X.

This paper provides a comprehensive literature survey of the overlap between ML for autonomous driving and V2V/V2X communications, with a focus on 5G. When nearby vehicles share data with each other, the performance of ML for driving tasks can be improved. However, V2V communications require the implementation of infrastructure to handle data transmission, as well as the adoption of specialized algorithms that can incorporate data from nearby vehicles as well as on-board sensors. Thus, our survey seeks to present an overview of current research supporting collaborative ML using V2V communications.

In this survey, we present the latest research in these areas, focusing mostly on papers from 2016 to 2021 and relying on older sources for contextualization. This research covers all aspects of improving ML using vehicular communications, from the communications technology to the algorithms for specific driving tasks. In this survey, we seek to answer the following questions to inform the integration of ML and V2V communications:

1) How can AVs effectively transmit data wirelessly on the road?
2) How do AVs manage the shared data?
3) How do AVs use shared data to improve their perception of the environment?
4) How do AVs use shared data to drive more safely and efficiently?
5) How can AVs protect the privacy of shared data and prevent cyberattacks?

By answering these questions, we provide a complete view of an autonomous driving system that incorporates collaborative ML algorithms.

A. Related Work

Several previous papers have surveyed the use of ML for V2V communication. Ye *et al.* survey ML techniques for common communication tasks, including traffic flow prediction, local data storage, network congestion control, load balancing, and resource allocation [5]. Similarly, Liang, Ye, and Li also present these topics in an ML framework in [6]. Tong *et al.* survey a broad list of potential AI applications for autonomous driving with communications, including cooperative parking, safety, demand-and-supply recommender systems, navigation, content delivery, and platooning.

Other authors survey more specific topics, including ML for V2I optimization [7], multi-agent reinforcement learning methods for vehicular communications [8], ML methods for cognitive radio vehicular networks [9], and ML for security in Internet-of-Vehicles [10]. In addition, Tang *et al.* discuss the potential for ML in 6G V2V communication [11].

B. Our Contribution to Literature

While existing survey papers explain how ML enables V2V communication, the *purpose* of communication is to allow collaboration between different vehicles on the road. Therefore, in this survey, we seek to combine existing literature on V2V communications and ML for autonomous driving into a coherent narrative that highlights current AV capability for collaboration in ML. Rather than surveying communications techniques or applications, we focus on the process of collaborative data sharing to improve the performance of ML algorithms in autonomous driving.

Thus, we outline the contributions of this paper in relation to previous survey papers as follows:

- Assuming a knowledge of basic machine learning techniques, this paper discusses more advanced deep learning algorithms than previous surveys, such as collaborative perception or multi-agent learning, and explores how these approaches can be used in the context of sharing data in V2V communications.
- We expand on certain topics not widely explored in general V2V communication surveys, including collaborative edge computing and security, and explore their connections to ML and V2V communications in general.
- Unlike previous survey papers, future challenges surrounding V2V communications and ML are a focus of this survey, which will guide future research directions.
- Most importantly, this paper unites advances across different fields to provide a broad understanding of how communication between vehicles can be used to collaboratively solve problems in autonomous driving and communication itself. Fig. 3 demonstrates the interconnected nature of these three research areas - this survey explores the connections between topics presented by other surveys to elucidate *how* challenges in one area can affect another in the context of autonomous driving.

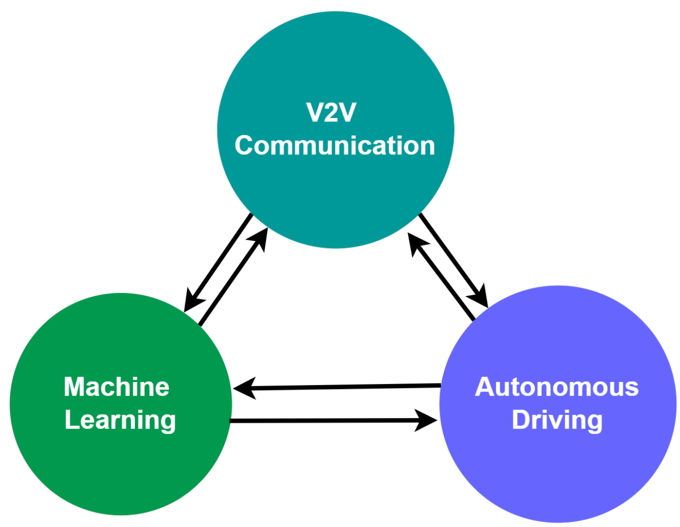

Fig. 3. Diagram demonstrating the interaction of techniques between ML, V2V communications, and autonomous driving.

First, **Section II, Machine Learning Overview** provides a basic background understanding of ML algorithms used in autonomous driving and V2V communications. This presents common ML problems which may be aided by the exchange of data in V2V communication. **Section III, How Vehicles Share Data** provides a general overview of the V2V communication technologies needed for AVs to exchange data. **Section IV, How Vehicles Manage Data** presents how vehicles jointly manage edge computing resources necessary for autonomous driving. The two major categories of AV collaboration problems, Perception and Driving, are presented in **Section V and Section VI, How Vehicles Collaborate**. **Section VII, Preventing Bad Actors** briefly presents research in preventing other collaborating agents from violating privacy or sabotaging vehicle operations. In **Section VIII, Training V2V-enabled ML Algorithms in Practice**, we present common datasets used to develop the algorithms discussed in the paper. Finally, we raise questions and future challenges in **Section IX, Discussion and Conclusions**. A framework graph for these sections is presented in Fig. 4.

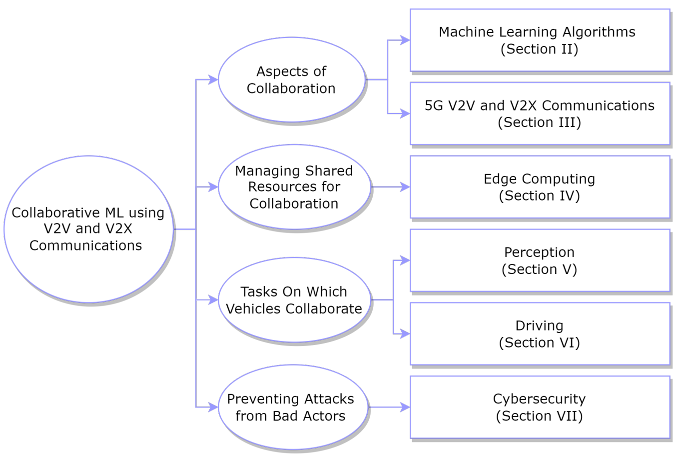

Fig. 4. Framework graph for the topics presented in this survey.

II. Machine Learning Overview

In order to drive as well as a human, AVs use ML to inform decisions. For example, ML algorithms can detect objects such as pedestrians, determine when to perform maneuvers such as turning or changing lanes, and even optimize wireless communications between vehicles. By communicating data with each other, AVs can improve ML performance. In this section, we present a general background of the ML algorithms used to solve autonomous driving problems as well as V2V communication problems.

In the past, research in ML for autonomous driving and V2V communications focused on classical techniques such as decision trees, gradient boosting, and Bayesian inference. Nowadays, however, AVs mostly rely on deep neural networks (DNNs) to control the vehicle [4]. Using many layers of artificial neurons, DNNs require much more data and computational power to train but can recognize more complex structures and represent a larger set of functions that cannot be captured by classical algorithms [12].

Deep learning is especially useful for processing high-dimensional data captured by the sensors of an autonomous vehicle [4]. Common deep learning algorithms include *convolutional neural networks (CNN)*, which are prevalent in the field of image processing; *long-short term memory networks (LSTM)*, which allow the use of sequences such as time series data [13]; and *deep Q-learning*, which is used in reinforcement learning tasks for optimizing behavior [14]. Self-driving cars currently rely on these deep neural networks to control four main aspects of driving: perception, high-level path planning, behavior arbitration, and learning-based motion control [4].

For perception, all AVs use deep learning to process image data collected by vehicle-mounted cameras [2]. AVs employ deep learning for image processing to map images into a scene of objects [4, 15]. Processing images requires ML for denoising and super-resolution, image segmentation, motion estimation, tracking, and pedestrian movement analysis. After processing road images, the AV can identify road markings and traffic signs, perceive road obstacles and weather conditions, and predict trajectories and plan responses accordingly [15].

Some AVs also use deep learning to process point cloud data. A point cloud is a dataset of 3D points that represent physical objects, typically gathered using a LiDAR sensor. AVs rely on deep neural networks for object detection and semantic segmentation, which constructs an environment from 3D point cloud data [4]. Since raw, unstructured point clouds have high dimensionality, AVs must structure point-cloud data so it may be used by deep-learning algorithms such as CNNs. Fernandes *et al.* describe five primary ways in which AVs may structure point clouds, depending on the task at hand. These include point-based, voxel-based, frustum-based, pillar-based, and projection-based. From this, both low- and high-dimensional features are extracted, which are then used in 3D object detection [16].

Once a driving scene has been constructed, the AV typically leverages reinforcement learning algorithms such as deep Q learning for driving decisions. Deep multi-agent reinforcement is the latest ML paradigm; this technique allows agents such as AVs to solve an ML problem by communicating with each other [17]. Multiple agents collaborating to solve an optimization problem is also known as decentralized optimization [18]. In addition, recent research explores deep learning for V2V communications tasks, as will be discussed in Section III. The rest of the survey will discuss how V2V communication can be used to improve the performance of the aforementioned ML algorithms.

III. How Vehicles Share Data: 5G V2V Communication

In order to share information, AVs must perform wireless data transmission. Here, we provide an overview of 5G V2V communication, which provides the low latency and high throughput necessary for communications between fast-moving vehicles [3]. 5G operates on higher bandwidth channels than previous generations of wireless communications and can support many more devices, enabling the formation of wireless ad-hoc V2V and V2X networks on the road. Furthermore, 5G supports *network slicing*, which allows the creation of virtual elements that can be chained together and deployed without physical installation. This supports different types of data sharing among AVs. For instance, critical V2V communications related to safety could operate on one network slice specifically created to support ultra-low latency and higher reliability standards, while less critical functions could operate on a different slice. 5G is the future of V2V networks, and in this section, we will discuss the system

TABLE I
ML ALGORITHMS USED TO ENABLE V2V COMMUNICATIONS

Application	Algorithm	Functionality	Source
Resource Provisioning	MDP with Policy Iteration	Minimize cost and overhead, maximize Quality of Service	[19]
	MDP with Bellman Equation	Minimize radio communication delay	[20]
	Historical-Based Reinforcement Learning	Optimize load balancing	[21]
	K-means++	Provisioning V2V radio channels	[22]
	MDP with Deep Q-Learning	Optimize channel selection and power levels	[23]
	DMARL with LSTM	Predict mobility and resource use of other vehicles	[24]
mmWave Beam Forming	Adaboost Deep Neural Network Deep Q-learning	mmWave beam attribute selection and prediction	[25]
	Linear Regression Support Vector Machine Random Forest Gradient Boosting	mmWave beam power prediction	[26]
	Deep Neural Network	Beamforming vector prediction	[27]
	Support Vector Machine	Beam selection	[28]
	Deep Reinforcement Learning		[29]
	Improved Fast Machine Learning		[30]
	Genetic Algorithm		[31]
	Deep Neural Network	Estimate beam quality	[32]
Data Caching	Deep Q-learning	Data caching resource optimization	[33]
	Kernel Ridge Regression	Predict cache allocation proportion	[34]
	Deep Deterministic Policy Gradient	Optimal cache allocation	[35, 36]
	Deep Neural Network	Optimize infotainment data caching	[37]
	Deep Reinforcement Learning	Optimize download speed Optimize caching with blockchain	[38] [39, 40]
Handoff	Fuzzy Q-learning Hidden Markov Model	Optimize communications handoff	[41]
	LSTM	Predicting signal strength	[42]
	Neural Network	Download rate prediction for handoff	[43]

requirements and challenges to overcome in implementing these V2V communications. ML algorithms that support V2V communications are summarized in Table I.

A. *Summary of 5G V2V Communication Technology*

5G technology is defined in 3rd Generation Partnership Project (3GPP) which constitutes the key services such as Ultra Reliable Low Latency Communication (URLCC) and enhanced Mobile Broadband (eMBB). Several research works highlight the diversified service requirements and sufficient spectrum resources of these 5G application scenarios for V2V applications. The 3GPP characterizes the basic URLLC reliability essentials for a single data frame of 32 as 99.9%, and an E2E latency of $\leq$1 ms [44] [45]. Based on resource sharing and mobility, the 5G use cases for vehicular communication can be classified as direct link V2V, Vehicle to Network (V2N), and V2N2V [46]. On the basis of range, power requirements, and application, we have used a top-down approach to survey the applications of 5G network in-vehicle communication.

Dedicated short-range communications (DSRC), supported by IEEE 802.11 Wireless Access in Vehicular Environments standards, used to be considered the de facto standard for vehicular communication [47] and is referenced by many academic sources in the field of V2V communications. However, DSRC has barely been deployed in the more than 20 years since adoption; because this spectrum has largely been unused, in 2020 the FCC announced a reallocation of the 5.9 GHz bandwidth [48]. As a result, researchers and automakers in the U.S. may be forced to switch to **C-V2X**, a communication standard similar to DSRC that instead relies on cellular or long-term evolution (LTE) and requires less bandwidth.

mmWave is a 5G communication technique that uses millimeter-length waves between 30 and 300 GHz for a variety of applications, including autonomous vehicle communications. mmWave can transmit large amounts of data quickly and is, therefore, an efficient communication method between AVs. Radio interfaces using mmWave have a wide bandwidth and allow for the use of beamforming [49, 50]. mmWave does possess several weaknesses - specifically, the waves have low communication power and are highly susceptible to interference. This may cause coverage holes due to the high mobility of AVs, which may inadvertently move out of communication range, and due to large vehicles like buses or trucks which may block the waves from traveling in the V2V network. Thus, beamforming and tracking techniques may be developed to solve these issues.

Architecture. The communication architecture for V2V can be designed similar to existing device-to-device (D2D) communication. The work of [51] has highlighted the advantages of D2D communication. Although D2D relieves the requirement of base station resources, improving the latency in short-range vehicular networks, this requires overhead to handle mode selection, peer selection, and environmental effects such as communication in non-line-of-sight (NLOS) situations.

At lower hardware levels, 5G is currently the best candidate for Multi Input Multi Output (MIMO) communication supported for Orthogonal Frequency Division Multiplexing (OFDM) architecture. One of the key technological features to support this is the ability of beamforming and beam steering supported by phased array antennas. In the 5G FR2 spectrum, which supports mmWave in the range of 28 GHz and 57 GHz, the antennas can generate pencil beams that support high throughput and minimum interference. However, in the V2V scenario, there are many challenges such as mobility, ultra-dense networks, and NLOS situations which make beamforming challenging. ML for beam steering and design of codebooks for beam alignments is an active area of research [52, 50].

In V2N, the higher levels in 5G architecture are capable to manage big data and computing power owing to their wide bandwidths. The recent breakthroughs in cloud-based ML have transformed all domains of autonomous driving, including vehicular communications. However, classical ML exerts severe demands in terms of energy, memory, and computing resources, limiting their adoption for resource-constrained edge devices. The work in [53] provides the relation between ML for communication and communication for ML for low-level 5G architecture. It discusses the limitations of hardware in terms of power consumption's and resources, thus using ML techniques for network edge computations. This can helpful for the infotainment services used in the vehicles, in supporting services for Connected Autonomous Vehicles (CAVs) such as traffic pattern recognition and long duration route planning.

Challenges communicating between vehicles. Implementations of V2V communication technologies in a vehicular network must overcome certain problems associated with transmitting data between vehicles. *Mobility* is one major issue. Because AVs are constantly moving, the structure of the vehicular network constantly changes, resulting in a dynamic vehicle ad-hoc network, or VANET, structure [54]. AVs must also calculate decisions quickly, in real-time; hence, the communication channel must have low *latency* so that transmitted data is still relevant by the time it reaches its target [3]. Furthermore, any errors in the AV system could lead to fatal consequences; as a result, incredibly high standards of safety must be met [55] and V2V communications must maintain greater standards of *reliability*. To overcome these channels, certain communication management techniques are outlined below.

B. Resource Provisioning and Allocation

Resource provisioning and allocation is the process by which wireless network resources such as time slots, frequency bands, and transmit power levels are made available for use in a network. Allocation refers to the process of making resources available to a specific user of the network, while provisioning involves users selecting how the resources will be used. In a V2V network, there may be many vehicles on the road, which may cause network congestion - this, combined with their constantly moving nature, may result in impairments such as shadowing, increased path loss, jamming, and interference [47].

Challenges in resource provisioning that may occur in a road scenario are depicted in Fig. 5. As shown, communications can be impaired by, for example, large distances, large vehicles such as buses or trucks blocking links, or high numbers of vehicles causing network traffic. AVs require high Quality of Service; as such, resources must be allocated automatically among users to minimize these impairments given a set of network conditions. In 5G networks with direct links between vehicles (known as sidelinks), Keshavamurthy *et al.* have defined a functional architecture to support V2V sidelink radio resource management that meets reliability requirements and reduces packet delay [56].

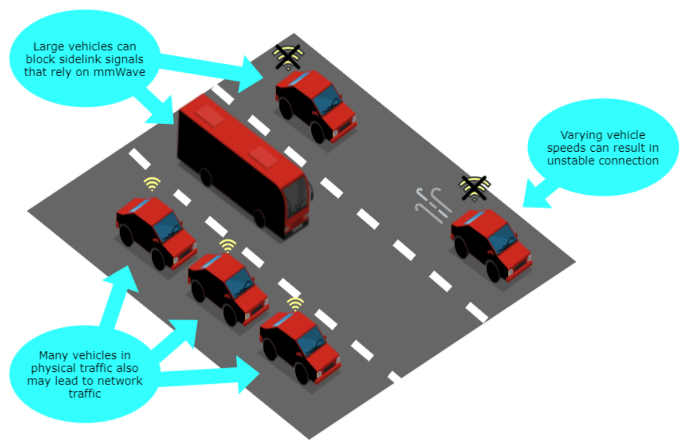

Fig. 5. Graphical illustration of potential V2V issues that can be addressed through resource provisioning, handoff, and mmWave beamforming.

ML algorithms can be used to support dynamic resource provisioning and allocation, which reacts to changes in service demand. Salahuddin and Guizani demonstrate how using reinforcement learning in a Markov Decision Process (MDP) can optimize resource allocation [19] in three ways: minimizing cost, maximizing Quality of Service for latency, and minimizing provisioning overhead. This optimization can be solved using techniques like policy iteration, Q-learning, or linear programming. Zheng *et al.* also optimize radio resource scheduling as a Markov decision process, which is solved using a Bellman Equation [20], and Ye, Li, and Juang developed a decentralized method in [23] that decides the optimal sub-bound and power level based on its own information, without a central controller. Li, Wang, and Jiang use online reinforcement learning for load balancing when vehicles are communicating with some fixed base station, which handles the problem that traffic in a particular area may vary at different points in time [21]. Chen *et al.* have developed the Adaptive Clustering and Scheduling for Dynamic Region-based Resource Allocation (ACSR) scheme, which provisions radio channels to be used in V2V networks depending on the geographic location of the AVs using K-means++ [22].

Other recent work focuses on using **deep reinforcement learning**. Ye, Li, and Juang developed a decentralized method in [23] that decides the optimal sub-bound and power level based on its own information, without a central controller. Each state transition is modeled as a Markov decision process, and deep Q-learning is used to process the input of the power level and spectrum subband of the V2V link in the network and, from there, determine the optimal policy to maximize reward. Similarly, Gündoğan uses deep multi-agent reinforcement learning to optimize transmission resources for a group of vehicles without requiring a base station [24]. Each vehicle (agent) predicts what resources the other vehicles will select to use, and adjusts their choice accordingly. An LSTM is used to predict mobility patterns of vehicles at each iteration of the algorithm, after which double deep Q-learning is used to evaluate the resource allocation policy and select which action to take. with experiences stored for future training [24].

Future potential. Because not every area will necessarily be outfitted with a base station to service AVs, deep multi-agent reinforcement learning appears to hold the most potential for the future of this research area. However, given the novelty of this ML method, more research is required to use and understand it effectively. Once the theoretical foundation of deep multi-agent reinforcement learning is more firmly established, and these models are more robust, they can be deployed in AVs to great effect.

C. Handoff

As mentioned, managing a vehicular network with many constantly moving vehicles is a challenge. One of the principal methods of mobility management involves handoff, or handover - the process of transferring an active communication session across a network. Because AVs are constantly moving in and out of range of each other, handoff may occur frequently in order to maintain communications. However, initiating handoff may be challenging - vehicles must decide when to hand off, select appropriate access points, and handle high overhead, among other issues [57]. Handoff may be imperative, meaning that it is required due to loss of connection, or alternate, where handoff is not required but does serve to improve communication. Imperative handoff may be reactive, thereby responding to changes in the network environment when they occur by handing off, or proactive, thereby using knowledge or mathematical modeling to predict when handoff must occur in the future. Alternate handoff may be horizontal, meaning that the type of technology stays the same, or it may be vertical, wherein a vehicle switches to a different communication technology [58].

Handoff can be optimized using **ML techniques**. An older technique for handoff is discussed by Xu *et al.* in [41], which uses fuzzy Q-learning to optimize communication throughput and adapt to various vehicle speeds and environments. Alam *et al.* review more recent methods, including reinforcement learning algorithms, k-means clustering, and game-theoretic algorithms [59]. Aljeri and Boukerche use an LSTM neural network to predict signal strength, with a stochastic Hidden Markov Model (Markov Decision Process) used to determine whether handoff should occur once a certain signal strength trigger is detected [42]. Similarly, Tan, Chen, and Sun use a neural network trained on attributes such as transmission rate, delay, bit error rate, vehicle speed, and packet loss to predict download rate for a potential network [43]. If the predicted download rate for another potential network is higher, then the communication is handed off. Using ML promotes accurate prediction of network use coupled with vehicle movement.

D. Beam Tracking

To improve mmWave communications, **beamforming** can be used to focus wireless transmissions and link vehicles more easily using directional antennas with lower transmit power [26]. In beamforming, radio waves are concentrated in a certain direction, rather than being transmitted in all directions - this increases transmission rates and thereby increases communication speed. It also allows for larger amounts of data to be communicated [60], which is important because sensors in AVs record vast data streams in real-time. Thus, large quantities of data must be transmitted in V2V communication. However, beamforming requires beam tracking - predicting the movement of the vehicle to which data will be transmitted so that the beam can be aimed properly - which can be challenging in an environment with constantly moving vehicles. To solve this problem, researchers have applied a variety of ML solutions.

ML algorithms. Klautau *et al.* generated an mmWave channel dataset and, in conjunction with the SUMO traffic simulator, which they used to test the performance of a variety of ML methods such as AdaBoost, Random Forest, Deep Neural Networks, and Deep Q-learning for predicting beam selection, estimating angles of departure and arrival of the beam to enable necessary beam tracking, and predicting channel evolution over time [25]. Wang, Narasimha, and Health propose an ML framework that uses vehicle locations and channel quality indicators as features to predict beam power and allow for situational awareness [26]. Similarly, Alkhateeb *et al.* propose a deep learning model for predicting beamforming vectors directly from signals received [27].

More recent research includes papers published in 2020 and 2021. Yang *et al.* use a support vector machine for selecting analog beams based on the average sum rate of potential transmission [28]. Chen *et al.* use deep reinforcement learning to overcome the problem of dynamic blockage, which is when other vehicles or pedestrians interfere with mmWave beams. Their solution optimizes beam training and data transmission by selecting the best non-line of sight path based on temporal data [29]. Gui *et al.* proposed an Improved Fast ML algorithm, which is a reinforcement learning algorithm that selects the optimal beam for mmWave communication [30]. Rasheed and Hu use a genetic algorithm to optimize beam selection and switch between 5G communication technologies when necessary [31]. Finally, Echigo *et al.* use deep neural networks to estimate beam quality for selection based on partial beam measurements and past beam sweeping [32]. These are just a sample of the many ML methods that have been developed for optimal mmWave beamforming.

Future potential. ML can be a valuable tool for enabling mmWave in V2V communications. For example, beam tracking requires predicting vehicle movements to ensure the transmitter and receiver are aligned - a problem that may be solved using an ML algorithm. In addition, beamforming and scheduling of mmWave communications may incur high overhead [61], and therefore ML algorithms may be employed to minimize overhead as well.

E. Data Caching

AVs rely on large amounts of data to operate effectively; thus, V2V data transmission can put great strain on network capacity and transmission may be very slow. As such, it is often desirable to cache data that must be frequently accessed. This involves storing data in a place that allows AVs easy and frequent access. Several different techniques and technologies have been developed for data caching. These include peer-to-peer cooperative caching, in which data is shared among vehicles currently on the road [62]; caching using roadside units or base stations, using Markov-chain models to decide whether cached data should be updated [63]; in-vehicle caching (IV-Cache), which relies on dynamic distributed storage relay to ensure the integrity of cached data and prevent data loss [64]; named data networking, which includes information on freshness or timespan of cached contents [65]; and blockchain [66].

Several **frameworks** for integrating caching into a V2V communication system have been developed. A framework proposed by He, Zhao, and Yin [33] allows for the AV system to jointly consider networking, caching, and computing resources and optimize resource allocation accordingly. This framework uses deep Q-learning to simplify the inputs (system parameters) and choose the best actions regarding how to cache data, use computing resources, and respond to requests from other AVs. Similarly, Wang, Yang, and Hu propose a framework for offloading traffic in ultra-dense networks. Their method proposes evaluating link quality using supervised learning and then using reinforcement learning to optimize the network traffic [67]. Varanasi and Chilukuri propose Flexi-Cache, a system that uses different caching methods depending on the type of data being cached; kernel ridge regression with self-learning predicts the proportion of the cache be allocated to each data type [34].

Advanced deep learning methods are also employed for caching. Deep deterministic policy gradient for reinforcement learning has been explored by Zhang *et al.* and Qiao *et al.* for optimal content processing and caching [68, 36]. Dai *et al.* combine custom deep reinforcement learning algorithms with blockchain to ensure that transmission of cached data is both fast and keeps identities of vehicles private [39, 40]. Finally, Ndikuamana *et al.* test deep learning methods for caching infotainment data in roadside units to improve communication latency [37], and similarly, Chen [38] design a custom adaptive reinforcement learning algorithm for optimizing download rates from roadside units. These data caching methods allow nearby vehicles to request data when necessary, ensuring communications transmit data fast enough for effective decision-making.

In the future, data caching can be employed to promote fast retrieval of commonly-used data in different scenarios. For example, data could be cached in roadside units constructed in areas of high network traffic, such as urban freeways. Or, data caching can be employed in vehicular data storage devices, to optimize resource use in V2V networks that must ensure strict Quality of Service requirements, including low latency. This will allow data to be transmitted more efficiently, improving the ML algorithms used to drive the AV. In the next section, we discuss how this data is managed in the driving environment.

IV. How Vehicles Manage Data: Edge Computing

V2V communication allows vehicles to exchange information on the fly and improve the performance of algorithms for driving decisions. However, processing such large quantities of data requires extensive computing resources and quickly accessible data storage. How can vehicles overcome this challenge? In this section, we explore how edge computing and V2V communications can be combined to increase the effectiveness of ML algorithms in AVs. The ML algorithms used for edge computing are summarized in Table II.

A. Edge Versus the Cloud

Cloud challenges. Tasks required to build and develop autonomous driving systems often require cloud computing resources. For example, building training data sets for ML models requires wireless transmitting large quantities of data collected by the vehicle to a centralized repository [82]. This results in high communication overhead and latency, especially given that vehicles are usually on the road and do not have access to stable wireless internet connections.

Edge computing is the process of performing computing operations in the physical location where the data and information are needed. The advantage of edge computing is that data transfer is faster than traditional cloud computing. Computation performed within the vehicular network itself results in improved latency and bandwidth consumption [83].

In this way, edge computing helps combine V2V communications with ML to build better AV systems. Depending on the context, in V2X communications, edge computing can refer to computing on the vehicle itself, or on roadside computing units that communicate with passing vehicles [84]. Detailed descriptions of the architecture required for vehicular edge computing can be found in [84, 83].

B. Using the Edge to Support V2V Communications

Improving communication latency. One advantage of edge computing is in minimizing latency. For example, tasks can be offloaded to edge resources using C-V2X communications [85], which is detailed by Bute *et al.* but originates from previous research in task offloading. To employ ML for

TABLE II
APPLICATIONS OF ML IN EDGE COMPUTING

Category	Algorithm	Functionality	Source
Classical Deep Learning to Support Edge Computing	CNN	Edge computing for model training	[69]
	Deep Q-learning	Optimize networking, caching and resource allocation	[70]
	Deep Deterministic Policy Gradient	Optimal cache allocation in edge computing	[35]
	Asynchronous Advantage Actor-Critic	Optimize video storage and sharing	[71, 72]
	Deep Neural Network Q-learning	V2V network communications routing	[73]
Federated Learning to Train Distributed Models	Two-timescale Deep Reinforcement Learning	Allocation of edge resources	[74]
	Variational Autoencoder	Proactive content caching on the edge	[75]
	CNN	mmWave beam selection	[76]
	Q-learning	Jamming defense	[77]
	Deep Q-Learning	Collaborative perception	[78]
	PointNet	Collaborative perception	[79]
	Neural Network	Privacy preservation	[80]
		Misbehavior detection	[81]

optimizing latency, Guleng *et al.* also propose a two-stage architecture for efficient communication routing in vehicular networks. In the first stage, a deep neural network predicts vehicle velocity and traffic density, and edge resources select how messages pass through the network. Then, the system evolves over time as Q-learning fine-tunes the parameters based on model performance [73]. Edge computing can decrease communication latency, but leveraging such resources requires optimizing resource use.

Managing resources. Similarly, ML models can be employed to optimize data storage and compute resources on the edge. Luo *et al.* discuss how, using deep Q-learning, vehicles with idle computing resources can support data processing for other vehicles, proposing a collaborative data scheduling scheme [70]. For the efficient caching of data in edge computing services, Zhang *et al.* propose a "deep critic cache network" for caching optimization [35]. This method is based on the concept of deep deterministic policy gradient - it uses a deep neural network to estimate policy and value functions for faster reinforcement learning. Furthermore, for resource allocation in V2V applications of blockchain, Jiang *et al.* employ an asynchronous advantage actor-critic (A3C) deep reinforcement learning algorithm [71, 72] to optimize storage and sharing of video data. This method may be employed to allow AVs to share massive quantities of video data for perception, as will be discussed in Section V.

Training ML on the edge. ML algorithms can even be trained on the vehicles themselves to avoid communication delay altogether. Hochstetler *et al.* demonstrate that a specialized device such as Intel Neural Compute Stick can support large CNNs for real-time video processing and object recognition, which is required by AVs [69]. On-vehicle computing resources are essential to the functionality of an AV and its V2V communications, and advances in these resources can enable ML functionality.

Other recent research in vehicular edge computing focuses on using **off-vehicle edge computing servers** to avoid problems with cloud delay when training ML algorithms. Zhu *et al.* explain edge learning, which is the use of servers near the vehicle to process data in real-time. Edge learning allows an ML model in a given vehicle to be aware of the context surrounding the vehicle. Claiming current communication paradigms to be insufficient in supporting edge learning, the authors of [82] propose *learning-driven communication* which uses federated learning to train ML algorithms within a vehicular network.

C. Federated Learning: Transmit Models, Not Data

Despite these recent advances in vehicular edge computing, training most ML models still requires vast quantities of data, far too much for vehicles to transmit via V2V communications in real-time. How, then, can vehicles collaboratively train ML models using edge computing resources?

Federated learning (FL) is the distributed training of an ML model where training data is contained across many edge computing nodes [86]. In FL, instead of aggregating large quantities of data in one place, model weights are distributed across nodes and updated with the local data. Then, the model weights are communicated between nodes and aggregated using a technique such as federated averaging. For more information on the details of FL functionality in driving applications, please refer to Zhu *et al.* [82] and Du *et al.* [87]. In this section, we explore how vehicular communications and FL can benefit existing autonomous driving algorithms.

Addressing operational problems. Ever-changing road conditions represent a challenge for training ML algorithms on AVs; algorithms need to be constantly trained on vast quantities of data in many different contexts, or else performance will degrade. In addition, data necessary for the training and operation of ML algorithms is very large and private in nature. By distributing model training across a vehicular network, FL can overcome these challenges [88]. Data is kept private, and model updates exchanged between vehicles can provide constant updates to neural networks used for driving decisions. Model training times are also reduced due to the distributed nature of the algorithm across many vehicles on the edge. Furthermore, by only transmitting model weights, communication overhead is reduced as well [89].

Current applications. FL supports efficient data sharing between vehicles. FL has been used to optimize resource allocation tasks in data transmission between vehicles and infrastructure [74]. For example, peer-to-peer FL has been applied to proactive content caching using a collaborative filtering-based variational autoencoder [75]. FL has also been applied to optimize mmWave beam selection [76]. In addition, FL has been utilized for collaborative perception [79, 78] as well as privacy preservation [90, 80] and cybersecurity in vehicles [77, 81], as is discussed further in Sections V and VII.

Implementing FL in AVs. Because ML is used to solve many disparate AV and V2V communication tasks, leveraging FL in a practical AV application will probably require a generalized framework. Zhang, Bosch, and Olsson develop an end-to-end on-device architecture for federated learning in vehicular environments, demonstrating that FL can achieve the same accuracy levels as traditional approaches with improvements in training and communication time [89]. In addition, Posner *et al.* propose a Federated Vehicular Network architecture for efficient FL, but this method is limited to venues with many stationary vehicles, such as large parking lots, and existing communications infrastructure [91]. Blockchain-based federated learning is proposed by Pokhrel and Choi; this technique promotes decentralized training with no adverse impacts from the failure of any individual vehicle to transfer data [92]. Of course, in considering these frameworks, further empirical investigation is required to determine the best format for on-vehicle FL.

FL challenges. While FL is a highly efficient solution for training ML on the vehicular edge, some drawbacks still persist. FL in the vehicular environment is challenging due to the communication issues discussed earlier: high vehicle mobility, strict Quality of Service, and necessity of efficient resource allocation, among others [87]. Moreover, FL in vehicular networks can also be challenging if datasets at individual nodes are highly imbalanced, or if certain vehicles fail to train the model after weight transmission. To overcome these problems, Wang, Liu, and Xia propose a method for selecting optimal vehicles and resource allocation based on a vehicle's individual data using a genetic algorithm [93]. Similarly, Deveaux *et al.* develop an approach to optimize selection of vehicles with high channel link quality and balanced datasets [94]. FL frameworks using V2V communication must incorporate such vehicle selection algorithms to ensure efficient performance.

D. Challenges in Edge Computing

Deploying edge resources to support V2V communications for ML requires overcoming several challenges. Here, we discuss current research addressing challenges in edge resource deployment.

Network densification. On a crowded roadway, many vehicles must communicate wirelessly using a limited spectrum. This forms a dense network wherein many wireless infrastructures are deployed in a small area. 5G communications overcome this problem. A 5G-enabled software-defined vehicular networking paradigm is proposed by Huang *et al.*, which relies on vehicular edge computing to provide enough computing power to support necessary services for AVs in a dense area [95]. In this way, mobile edge computing can support network densification.

Where to deploy roadside units. In the future, urban areas may construct computing units on busy roads, to which vehicles can offload computing. These are known as roadside units (RSUs). How can we select the optimal location to place these units? In support of optimal placement of mobile edge computing resources, Moubayed *et al.* formulate a Greedy V2X Service Placement Algorithm [96]. This algorithm solves the binary integer linear programming problem to determine how best to place edge computing units to support V2V communications.

Power consumption. Mobile edge computing is power-intensive, which can be problematic considering most electric AVs and RSUs currently have limited battery capacity. Dong *et al.* develop an energy-efficient approach for scheduling tasks using deep reinforcement learning [97]. The optimization algorithm minimizes both power consumption and latency in task scheduling for Non-Orthogonal Multiple Access (NOMA) communications with RSUs.

E. The Future of Vehicular Edge Computing

Edge computing and ML go hand-in-hand for enabling vehicular communications. Edge computing resources can provide the computational power necessary to use large-scale ML models in AVs, but ML can also help enable the functionality of edge computing.

In the future, edge computing resources may be applied to support ML solutions across all challenges in autonomous driving - both related to communications and vehicle control. Edge computing resources can allow the deployment of more computationally-intensive ML methods for cybersecurity, resource provisioning, and other problems in enabling V2V communications. Federated learning will enable vehicles to train ML models on the edge, without requiring data transmission between cloud servers. To accomplish this, edge computing methods and a robust federated learning framework must be integrated and tested within a fully functional autonomous driving system.

V. How Vehicles Collaborate: Perception

Before executing driving maneuvers, an AV must first convert data collected via sensors into a scene representing the surrounding world. This perception process is known as *driving scene understanding*. By communicating wirelessly, AVs can improve perception - for example, by warning other vehicles of upcoming road hazards. This requires data shared via V2V communication to be incorporated into the AV's internal representation of their driving environment using ML.

ML algorithms that rely on data from multiple collaborating vehicles for driving scene understanding are summarized in Table III. These mostly revolve around incorporating shared data from other vehicles with pre-trained image recognition algorithms such as YOLO [98] and other CNNs. In the following sections, we describe how such algorithms are used for autonomous driving and how they may incorporate data transmitted wirelessly from other vehicles for driving tasks such as object recognition.

TABLE III
ML ALGORITHMS FOR DRIVING SCENE UNDERSTANDING WITH V2V COMMUNICATIONS

Category	Algorithm	Function	Source
Cooperative Perception	Mobilenets SSD	Collaborative object detection	[99]
	YOLO, DenseNet	Collaborative object detection and classification	[100]
	CNN	Occluded object detection	[101]
	CNN	Optimizing data selection for transmission	[102]
	YOLO	Object detection via traffic camera for data fusion	[103]
	Deep Reinforcement Learning	Optimizing data selection for transmission	[102]
	Domain Adaptive YOLO	Object detection with blockchain	[104]
	Deep Q-Learning	Optimizing latency in data sharing	[78]
	PointNet	Road user classification	[79]
Data Fusion	Support Vector Machine	Fusing LiDAR and camera data	[105]
	Deep neural network	Object detection framework	[106]
	Deep neural network	Review of potential applications	[107]

A. Driving Scene Understanding Overview

Within the decision-making architecture of a self-driving car, the first step is called *perception*. This refers to using ML coupled with data from sensors such as cameras, LiDAR, radar, or a fusion of such sensor-based data sources to observe and extract features of the environment around the vehicles [4]. These features might include other vehicles, road markings, signs, or obstacles. Detecting these features is referred to as *driving scene understanding*, or “driving scene uptake,” and is typically performed using various deep learning architectures, including pre-trained CNN models. For example, in [108], ML is used to detect pedestrians and predict their trajectory - where they are going and how they are moving. Once these features are observed, they are then mapped into a driving environment, and the AV can make decisions based on this environment that has been observed [15].

One major aspect of driving scene understanding is **feature detection**. To detect important objects in an image, feature detection algorithms draw bounding boxes around objects in an image to identify them. Once features are detected, **semantic segmentation** marks the pixels of an image as representing different objects such as drivable areas, pedestrians, traffic participants, and so forth. The technique of localization seeks to calculate the position and orientation of the AV on the road and can be accomplished using common systems such as GPS, or by using deep learning algorithms to process image and LiDAR data [4]. Other important techniques include data fusion - combining multiple sources of data to detect and map objects - as well as depth estimation, where the vehicle tries to use multiple images to estimate their distance [15]. All of these techniques are necessary for driving decisions, and these are enabled through ML. The more accurate these techniques are, the more safely and efficiently the AV can drive. Therefore, these techniques are prime for the incorporation of external data via V2V communication.

Feature detection allows AVs to accurately perceive their environment. This allows for the fast and safe completion of various tasks such as obeying traffic rules, planning routes, and avoiding collisions. Even though AVs are outfitted with multiple cameras for varying view angles, it is still possible for a vehicle’s view to be occluded if an important object is hidden behind some other obstacle. This is why methods for integrating data from other vehicles using V2V communications are necessary - to increase driving safety through high-quality driving scene understanding. These include data fusion methods and cooperative perception algorithms.

B. Data Fusion

Data fusion is the process of combining many sources of data. This is essential in ML for V2V communications as AVs rely on many sensors, including LiDAR, radar, cameras, GPS, and wheel odometry. Multisensor data fusion techniques have been in development for decades [109], but more recently, ML for data fusion has been applied in V2V contexts [110, 111]. When focused on data collected from sensors, the process is also known as sensor fusion. Data fusion allows complex sensor data to be combined into a complete, global view of the AV system and more specific and useful knowledge to be extracted. The data fusion process is depicted in Fig. 6. In addition to combining data from multiple sensors, data fusion can also combine data from multiple nearby vehicles using V2V communications.

ML for data fusion. Though traditional ML models have been used, most data fusion methods rely on deep neural networks. Previously, Rubaiyat *et al.* have discussed using support vector machines in fusing LiDAR and camera data for object detection [105]. However, more recently, Fayyad *et al.* surveyed deep neural networks for data fusion in environmental perception, localization, and mapping - they provide an exceptional summary of the advantages of deep learning in this area [107]. In the context of V2V communication, Marvasti *et al.* have developed a framework wherein the features of deep CNN models are shared between communicating vehicles to improve object detection in AVs [106]. By sharing detected feature maps between vehicles, features that are occluded from one vehicle’s sensors may be detected and used in control planning. Since V2V communications may transmit a large quantity and variety of data, data fusion techniques will be essential for ensuring that transmitted data from other vehicles may be combined with the vehicle’s own sensor data to improve driving.

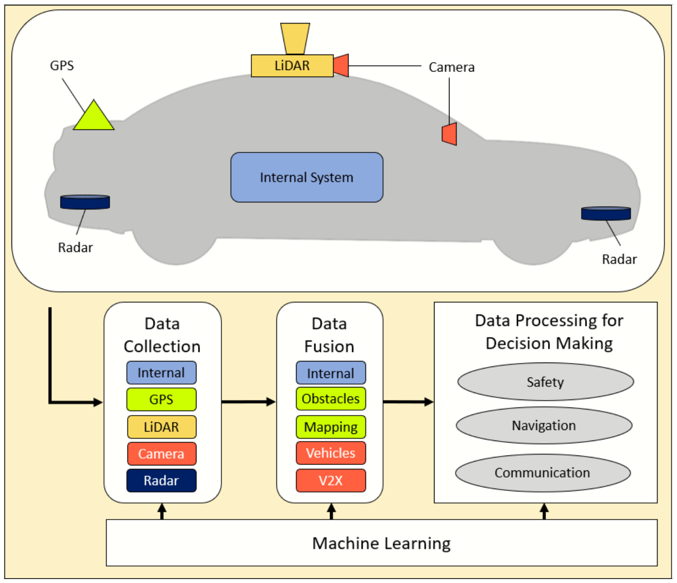

Fig. 6. Diagram depicting all aspects of the data fusion process in AVs, including sensors employed by the vehicle. Note that machine learning is used at each step of the data fusion process.

Data fusion challenges. Challenges in data fusion include the complexity of the data collected, the large number of questions that may be answered by the data, and the difficulty in achieving simultaneous optimal exploitation of each set of data [110]. For example, because AVs are outfitted with dozens of sensors, complementary information from these sensors can be combined in different ways to generate useful features, such as location and velocity of surrounding vehicles and obstacles, road conditions, and lanes [107, 111]. Communication issues also must be considered. Lee *et al.* demonstrate that packet loss and delay can cause significant negative impacts on data fusion performance in V2V networks, and propose memory-based methods for enhancing data fusion [112].

Engineering a data fusion system for real-time use is challenging. AV sensors collect massive quantities of data each second, meaning that ML models for data fusion must be able to perform inference in real-time, which limits their complexity. Vehicles are also not limited to one representation of objects in the environment. As outlined by Fayyad *et al.* different localization methods may be used to accomplish various goals; any ML algorithm for data fusion must be able to handle different types of localization. Thus, during implementation, engineers must select the best representation for their system [107].

C. Cooperative Perception Algorithms

In cooperative perception, vehicles use shared and fused data to improve the perception algorithms that define the vehicle's understanding of the environment. By incorporating additional data from other vehicles, the neural networks that identify objects can achieve improved performance. Here, we outline research seeking to improve cooperative perception among vehicles in a V2V or V2X network.

Collaborative vision techniques allow multiple vehicles to share image data from their cameras to effectively overcome occlusion and extend their range of vision. Yee *et al.* propose an algorithm enabling collaborative vision using pre-trained models [99]. The study considers SSD Mobilenets and YOLO for object detection. Instead of sharing raw data, objects are processed and locations are transmitted to other vehicles to reduce bandwidth requirements. Similarly, Rawashdeh and Wang propose using communicated data to construct an extended view of vehicle surroundings, which is then integrated into the object tracking system [100]. This method relies on YOLO for constructing bounding boxes, and DenseNet for object classification. When an object such as a specific make and model of a car is recognized, the system can approximate the dimensions of the object in order to calculate where it would be located in the scene. Models can also be shared with other vehicles, as discussed by Jiang *et al.*, who use blockchain for model sharing with DA-YOLO for object detection [104].

Selecting data to be transmitted. AVs collect vast quantities of data, and to optimize the use of channel bandwidth, it may be necessary to share only a subset of data. Wang *et al.* propose a system for efficient data fusion which compresses feature maps using a CNN; since communications require fewer resources as less data is transmitted, vehicles can share data more quickly [101]. They also provide a multi-vehicle dataset, V2VNet, for training ML models for V2V communications. Alternatively, if certain data has higher importance than others, it may optimal to give priority to more important transmissions by canceling or delaying others. Higuchi *et al.* demonstrate how *value-anticipating networking*, wherein senders evaluate the potential value of their wireless messages compared to others [113], is able to improve cooperative object tracking performance.

Other authors propose integrated ML systems for selecting data to be transmitted. Krammer *et al.* propose a system called Proventia that uses traffic cameras to construct an Intelligent Infrastructure System, which communicates traffic data from cameras and radar to nearby vehicles using a roadside unit [103]. Edge devices detect objects using YOLOv4 and communicate these objects to passing vehicles, extending their perception. Aoki, Higuchi, and Altintas propose the Cooperative and Intelligent Vehicle Simulation (CIVS) Platform which integrates the traffic model, vehicle model, communication model, and object classification model to train CNNs for deep reinforcement learning [102]. This combines the SUMO traffic simulator, CARLA vehicle simulator, and YOLO object classifier which provide inputs into a Deep Reinforcement Learning Cooperative Perception simulator to optimize which data is transmitted to nearby vehicles. CIVS allows cooperative perception to rely on fewer communication resources.

Federated learning has also been applied for collaborative computer vision, to allow vehicles to efficiently transmit vision models for training. Barbieri *et al.* develop a method to use Lidar data and federated optimization for point cloud classification [79]. This method improves classification accuracy by allowing nearby vehicles to share model weights. Li *et al.* explore methods for minimizing transmission latency and propose a method for collaborative data sharing using federated learning [78]. By using federated learning, many models distributed across vehicles can be updated without requiring massive data transfer.

Advantages of cooperative perception. How well does ML for cooperative perception improve safety? In an empirical study testing the performance of an environmental perception message system with European V2X standards, Miucic *et al.* find that a V2X communication system can improve response times of multiple vehicle safety applications. These include emergency electronic brake lights, intersection movement assist, blind-spot warning, and left turn assist [114]. Using a simulated V2V cooperative perception system, Yoon *et al.* also find that communication can improve perception in highway and roundabout scenarios - but only up to a certain point. If too many vehicles participate in data sharing, network traffic will increase without yielding improvements in accuracy on perception tasks [115]. Hence, to effectively use cooperative perception, researchers must develop new methods which minimize communication overhead in cooperative perception.

D. Future Potential of Cooperative Perception

Cooperative perception can improve ML performance, but transmitting large quantities of sensor data wirelessly causes network traffic and is too slow to be reliable. Furthermore, localizing and processing large quantities of data to provide as inputs to ML models can also be slow. Though current research has started to address these concerns, if the cooperative perception paradigm is to be extended broadly to ML for tasks such as detecting objects to avoid collisions, future research ought to focus more intensely on this area.

Consider feature detection, a task at which even cutting edge ML performance is less than desirable [116]. Since this task is performed by CNNs, rather than wasting communication resources sharing raw data, it is preferable to transmit feature maps from the CNNs on each vehicle, since such data is smaller and more relevant to the task at hand - this process is discussed by Yang *et al*. Of course, combining feature maps from numerous outside sources is difficult. The process raises a host of challenges, including synchronizing feature maps from multiple senders, efficiently compressing and streaming feature maps, and selecting which feature maps would be the most valuable to the recipient [116]. Developing new ML techniques that overcome these challenges will allow important data to be shared more efficiently in cooperative perception.

AV systems that integrate ML for cooperative perception into all aspects of their performance will experience increased performance on driving tasks. Extending studies of value-anticipating networking [113] to other ML problems such as feature detection can provide further insights into how AVs might transmit only data that is essential to these ML algorithms. This will reduce communication resource use and ease localization burdens. Furthermore, while ML systems like the CIVS platform optimize data transmission, the next step is to implement proposed ML methods for data fusion and cooperative perception methods in a practical setting, train the ML algorithms on larger datasets, and compare performances.

Finally, although the current market share for cooperative perception using vehicular communications will require time to mature [114], further standardization of different communication protocols between vehicles is necessary to optimize future ML performance in AVs. Cooperative perception will improve the safety and efficiency of autonomous driving [117].

VI. How Vehicles Collaborate: Driving

Driving maneuvers are complex: human drivers use abstract symbols, such as flashing high beams or edging out into traffic, to cooperatively solve problems on the road. Autonomous driving algorithms for singular vehicles are well-studied, and thus lie outside our scope. However, cutting-edge ML techniques coupled with V2V communications technologies allow vehicles to cooperate on the road like humans to avoid collisions, reduce traffic, and perform other functions. In this section, we discuss how V2V communications and reinforcement learning can be combined to allow vehicles to collaborate on complex driving decisions. Algorithms from this section are summarized in Table IV.

A. Safety and Collision Avoidance

Multiple AVs can work together to ensure driver safety. Modern vehicles must comply with many safety standards in order to drive safely [126]. Ideally, however, AVs should not simply meet minimum standards, but also incorporate additional safety features to ensure they are trusted by consumers and are commercially viable. Currently, AVs are generally driven by deep learning-based control systems, which process sensor data such as camera images as input into a neural network, and output the optimal driving action, such as steering, changing speed, or stopping [127]. These systems can be aided by V2V communications.

System data sharing. By sharing data about potential vehicular failures, AVs can warn other vehicles in advance of problems that might result in a traffic accident. In addition to cameras and LiDAR sensors for collision avoidance, modern AVs include many common safety features including anti-lock braking, traction control, and electronic stability, and use sensors to collect system data and detect mechanical failures. This data can be shared with nearby vehicles to quickly provide information in case a problem occurs [128]. The Multi-Car Cooperative Collision Avoidance project has developed a system to allow a network of vehicles to share data for collision avoidance [129] where braking is insufficient to avoid an accident. These advances improve driving safety using V2V communication.

Environment data sharing. In addition to internal system data, V2V communications also enable multiple vehicles to transmit information about the driving environment. For example, one vehicle may inform another of a dangerous situation on the road that is not immediately detectable [130]. Or, one vehicle may be able to correct data input that is adversarial to another vehicle's control system. These types of systems have been proposed as early as 2010 by Mitropoulos *et al.* who develop a wireless local danger warning system to transmit warnings about dangerous areas to AVs [131].

External data can then be leveraged for **safety prediction.** Determining road safety involves tasks such as analyzing

TABLE IV
ML Algorithms Used to Leverage V2V Communications in Collaborative Driving

Category	Algorithm	Function	Source
Safety and Collision Avoidance	CNN	Road safety prediction	[118]
	Kalman Filter	Fusing vehicle perception data	[119]
	Deep Neural Network	Rear-end collision prediction using V2V data	[120]
	Bayesian inference	Predicting collisions	[121]
	K-medoid clustering	Estimating collision probability	[122]
	Decision tree	Collision detection and driver fatigue detection	[123]
Collaborative Traffic	Deep Q-learning	Highway traffic optimization	[124]
	Evolutionary Algorithms	Coordinating driving behaviors on unmarked roads	[125]

driving behavior, detecting vehicle surroundings, modeling the road, and analyzing road images [118]. These tasks can be enhanced via additional data from other vehicles. As one example, Chen *et al.* demonstrate how deep neural networks can predict rear-end collisions based on V2V communications [120]. They also demonstrate the use of a Kalman filter to fuse perception data from nearby vehicles for safer driving [119].

Similarly, Peng *et al.* propose a deep learning approach, the DeepRSI framework, to improve safety. In this model, CNNs on multiple vehicles process GPS trajectory and environment data to predict traffic flow; outputs are communicated and fused with data from other vehicles for improved accuracy [118]. Furthermore, Yu and Petnga have developed a space-based collision avoidance framework that relies on V2V communications with spatial and temporal data, though the use of ML for the system is still in development [132].

Detecting driver fatigue. Though fully autonomous vehicles are the ultimate goal, current and upcoming autonomous driving technology still require aware drivers to take the wheel when necessary. Li uses a decision tree coupled with V2V communications and other sensors such as Li-Fi to detect driver fatigue in intelligent vehicles and alert drivers of potential collisions or unsafe behavior [123].

Overcoming challenges. System and environment data transmissions in a dynamic vehicular environment may not always be reliable, which has prompted ML methods to address communications issues. For example, the non-parametric Bayesian inference method in [121] predicts crashes while mitigating the effect of data loss from communications. In addition, a technique by Haider *et al.* clusters vehicles into groups using a modified k-medoid [122] for more efficient estimation of collision probability.

Future potential. Current research demonstrates how V2V communications can improve collision avoidance in AVs. In the future, even advanced methods like deep Q-learning that do not leverage data sharing in a vehicular network may be improved by V2V communication [133, 134, 135]. The next step in using V2V communications is to determine how to incorporate these prediction algorithms into a fully functional AV system and test them empirically.

B. Collaborative Traffic

Traffic congestion is a major issue in transportation, slowing down travel and reducing fuel efficiency. By communicating with each other, AVs can coordinate their driving such that traffic jam frequency is reduced and any traffic that does occur resolves more quickly [136, 137, 138]. This is referred to as collaborative traffic.

Collaborative traffic research efforts can be divided into two distinct foci: urban traffic and highway (or freeway) traffic. These differ in that urban roadways feature controlled traffic intersections, while highways do not have controlled intersections but do require merging and exiting a moving flow of traffic. As demonstrated by traffic simulations, by adopting collaborative strategies and working together, AVs have the potential to decrease traffic and increase road capacities in urban environments [139] and on highways [140]. As described by Autili *et al.*, communications between vehicles can help AVs choreograph their movements to improve traffic flow [138].

Optimal traffic control. Researchers have developed methods for AVs to resolve a variety of traffic issues quickly. For deadlocked traffic, Wang *et al.* propose Altruistic Cooperative Driving [137]. For faster highway merging, Xie *et al.* demonstrate that V2V communication can improve traffic flow and reduce accidents at highway on-ramps [141]. Other research on resolving traffic represented a group of AVs as a multi-agent system that uses inter-vehicular communication to move vehicles synchronously [142].

Vehicle platooning is also supported by V2V communications. This behavior involves coordinating movements among a group of several nearby vehicles [143, 144, 145]. The technique has been studied for decades, as it provides several benefits such as higher road utilization, which reduces traffic, as well as less wind resistance, which reduces fuel consumption [143]. Recent studies focus on how AVs can form and maintain safe and effective platoons automatically, without requiring the driver [144]. V2V communications have been found especially useful for controlling AV platoons [145]. Given the vast quantities of data collected by AVs, these platoons may be improved through the implementation of V2V communication and ML.

Unfortunately, **advanced methods for traffic control** have been relatively ineffective. Chandramohan *et al.* discuss the use of deep Q-learning for cooperative driving in AVs [124]. This study simulates AVs which cooperatively control each other's speeds using V2V communications; however, this method results in an unacceptably high collision rate (30%). Huang *et al.* use evolutionary algorithms to develop an

AV controller able to navigate on an AV-only road while minimizing collisions [125]. The automatically-synthesized optimal behavior could be communicated to vehicles entering a certain area; unfortunately, however, results show this type of optimization is also not particularly effective.

Future potential. Based on the limited research success in this area, much more work will be necessary in order to leverage ML and V2V communications for road traffic reduction. Researchers have investigated how deep reinforcement learning can be used to optimize speed and reduce traffic, such as in [135, 134, 146], but methods successfully using V2V communication are still scarce. Furthermore, V2V communication has not been applied to other unique AV tasks such as collaborative parking [147, 148].

While AVs can synchronize behavior to reach their destination faster, few works examine potential solutions to accomplish this goal. Synchronizing the behavior of many independent agents to optimize some value - in this case, road traffic - is a challenging task; thus, there is great potential in this area of ML and V2V communication research.

C. Multi-Agent Learning

V2V communications allow AVs to coordinate their movements for tasks such as traffic reduction, but such actions require an optimization technique that supports collaboration between multiple agents. In this section, we explore multi-agent techniques that may resolve some of the AV collaboration issues presented earlier.

Deep multi-agent reinforcement learning (DMARL) is a major area of potential for collaborative driving. In DMARL, each agent uses a deep reinforcement learning technique such as deep Q-learning in order to optimize some function. However, in addition to interacting with their environment, agents can also communicate with each other [17]. Multiple agents collaborating to solve an optimization problem is also known as decentralized optimization [18]. DMARL for AVs is depicted in Fig. 7; here, each vehicle acts as an agent, learning rewards from the state of the driving environment after taking certain actions.

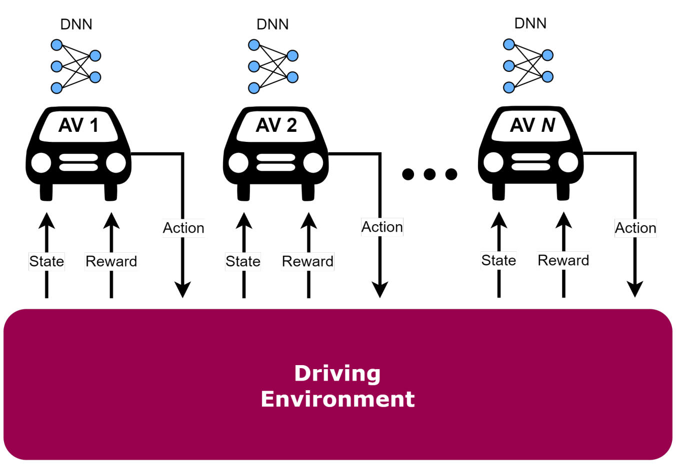

Fig. 7. Depiction of deep multi-agent reinforcement learning for AVs. Each vehicle trains an individual DNN based on interactions with the driving environment that change the environment state and yield some reward.

The problem of nonstationarity. An early model for multi-agent learning is described by Tan *et al.* in [149], which proposes independent Q-learning (IQL) wherein each agent learns the optimal policy separately, treating other agents as a part of the environment. However, this poses a major issue in that, as agent behavior changes, the environment becomes nonstationary and the algorithm cannot converge to optimal behavior. Furthermore, Deep-Q learning is often used to address extremely large state spaces - this technique involves approximating the Q function by a deep neural network to reduce the state space or the information required to make the decision [14]. It requires replaying previously stored memories, which further exacerbates the problem of nonstationarity in multi-agent reinforcement learning.

Overcoming the nonstationarity problem is essential for multi-agent methods. The model architecture proposed in [17] for multi-agent reinforcement learning reduces this problem by allowing agents to learn optimal communication protocols and communicate information about their own states. Foerster also discusses multiple approaches to this issue in a more recent paper [150]. One approach considers memories as decaying "off-environment" data that eventually become obsolete. Another approach allows an agent to learn a conditional policy based on the policies adopted by other agents. Further advances will no doubt address this issue as well.

Multi-agent computational issues. Another issue with distributed optimization algorithms such as DMARL is communication time, which imposes overhead and delays the algorithm, especially when one node in the network of agents is especially slow. These problems are addressed in [18] which proposes the QuanTimed-DSGD algorithm, imposing a deadline on calculations from agents for optimization and communicating quantized versions of internal models to improve communication overhead. Along these lines, [151] introduces Variance Based Control for DMARL, which reduces communication overhead by creating a policy such that agents only communicate when their confidence in the decision is low, and only send messages when the information within is informative. These advances in DMARL are promising and may contemporize V2V applications.

D. Future Theoretical Improvements

As statistical and computational issues with DMARL are remedied, DMARL can be applied to many of the previous issues with collaborative driving. For example, in a DMARL framework, AVs would be able to more effectively incorporate data from other vehicles shared via V2V communication. This would improve optimization algorithms within individual vehicles, potentially overcoming the poor performance seen in previous papers [124, 125]. Because the method intrinsically models communication between multiple agents, DMARL appears to be the most promising method for future research in collaborative driving with V2V communication, though it will require theoretical work to ensure convergence in difficult problems.

TABLE V
ML ALGORITHMS USED TO ENSURE V2V COMMUNICATION SECURITY

Application	Algorithm	Functionality	Source
Anomaly Detection	Deep Neural Network	Packet anomalies	[152]
	LSTM Network		[153]
	CNN	Network traffic anomalies	[154]
Attack Prevention	Federated Learning, Neural Network	Privacy preservation	[80]
		Misbehavior detection	[81]
	Q-learning	Jamming defense	[77]

VII. PREVENTING BAD ACTORS: COMMUNICATION SECURITY

In order to implement V2V communications, an AV system must feature strong cybersecurity precautions. While our discussion so far has espoused the benefits of V2V communication, one drawback of vehicular networks is the potential for bad actors. Because AVs do not necessarily know the identity of other vehicles with whom communications are transmitted, it is possible for malicious users to engage in cyberattacks to sabotage the performance of other vehicles in the network, potentially harming road users. In this section, we provide a brief discussion of potential cybersecurity issues surrounding the use of V2V communications for ML algorithms in autonomous driving as well as the most common security techniques that address these issues. ML algorithms for security are summarized in Table V.

A. Common Cybersecurity Threats

There exist four cybersecurity challenges especially pertinent in V2V applications. These include *unpredictable attack scenarios*, which result from the many virtual entry points to the vehicle using communication; *high safety risk*, which occurs due to the dangerous nature of driving a vehicle and potential for accidental injury or death; *limited connectivity*, resulting from the inability of vehicles to frequently update their operating systems; and *limited computational performance*, which limits potential solutions to those with low overhead. These attacks can target the control, communication, or sensing systems in the vehicle [155].

According to Abu-Talib *et al.*, the four major attack targets include the following: integrity, where attackers spread false information or tamper with messages; authenticity, where an attacker creates a false identity; confidentiality, where the attacker records the ID of vehicles; and availability, where attackers jam the signal or deny service by overwhelming the vehicle with many false messages [156]. These are depicted in Fig. 8.

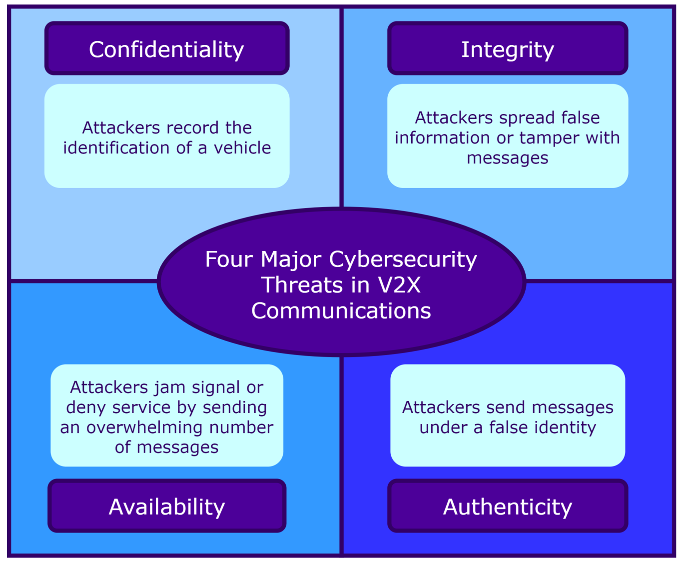

Fig. 8. The four major types of cybersecurity threats in V2X networks.

Classical solutions. To prevent cyberattacks, an AV must first ensure its data transmissions are secure. This can be accomplished using cryptographic digital certificates to authenticate messages, physically detecting vehicles before accepting messages from them, and using trust models to evaluate the truthfulness of a message before accepting it [156]. A secure V2V communication model, the cooperative full-duplex non-orthogonal multi-access (FD-NOMA) model, is proposed by Wei *et al.* in [157]. Concurrently, blockchain technology is proposed for secure data sharing in V2V networks in [158] and [159] in order to protect vehicle security and privacy when sharing and storing messages.

Machine learning, however, has the potential to solve many problems in vehicular cybersecurity. Current research most commonly considers ML for anomaly detection. Deep neural networks can perform robust detection by processing large data streams. Deep learning models are also useful for classifying types of malware, simulating attacks, defending against adversarial visual attacks on sensors such as cameras, and providing fallback solutions for safe driving in case an intrusion does occur [155]. Such algorithms can also be optimized using federated learning as in [81], which presents an algorithm for detecting data falsification. Preventing the transmission of fake data that may damage cooperative perception and driving efforts is imperative for V2V communications to effectively benefit autonomous driving.

Anomaly detection in vehicular communication. Using deep learning for anomaly detection is not new, having been addressed in the past by Kang and Kang [152] and Taylor, Leblanc, and Japkowicz [153]. In [152], researchers trained a deep neural network to detect malicious packets using the Open Car Testbed and Network Experiments (OCTANE). This model uses features extracted from the bitstream of the V2V network and pre-trained parameters created using a Restricted Boltzmann Machine to improve the convergence speed of the deep neural network. Similarly, an LSTM neural network is used in [153] to predict packet data values and detect anomalies; the model is trained on 19 hours of driving data. This model prevents attackers from exploiting the CAN bus, which communicates to the vehicle control system wirelessly, to take control of a moving vehicle, thus protecting the vehicle from dangerous outside malfeasance. More recently, Nie, Li, and Kong used a CNN for extracting spatiotemporal network features to use for predicting network traffic [154]. V2V networks have much shorter timescales of communication, and this method addresses the issue by extracting more features from the short-range traffic to account for the short lifespan of communication. This helps detect malicious anomalies in network traffic more precisely, helping prevent obviously incorrect information from being transmitted in a given network.

Future potential. Despite these works, a vast amount of work still remains in ensuring the security of V2V communications. Several challenges are outlined in [155] - in general, these include ML for detecting and preventing spoofing and intrusion attacks, disruption and jamming attacks on the communication system itself, and denial-of-service attacks on communications with cloud-based databases. Furthermore, one exceptional challenge is that, when AVs form a network such as in a platoon, they must be able to recognize and prevent attackers from sharing false data that causes them to make adverse decisions. For instance, a bad actor could warn other vehicles of a nonexistent obstacle, slowing traffic and potentially causing accidents as a result. Similarly, adversarial attacks are another concern; attackers can artificially construct specific inputs that trigger ML algorithms to malfunction, possibly causing danger to passengers. These must also be detected and prevented by AV security systems.

B. Data Privacy

Even if attackers do not seek to harm other vehicles on the road, they can still potentially collect and store massive quantities of data transmitted using V2V communications. Privacy is an important concern for many consumers as vehicular data can reveal personal information, such as locations to which one frequently travels. Maintaining data privacy is, therefore, a major hurdle to overcome in the deployment of collaborative ML using V2V communications. How can we maintain user privacy in the context of V2V data sharing?

As mentioned previously, **federated learning** is one powerful solution for data privacy [80]. By sharing model weights instead of data, federated optimization algorithms ensure that no private data is shared. This method can also be used in conjunction with differential privacy, which is a method of sharing group patterns while preserving information about individuals [160]. This protects the privacy of even the model parameters, preventing attackers from reverse-engineering data based on model updates. Olowononi, Rawat, and Liu employ federated learning with differential privacy using the Laplace mechanism and layer-wise relevance propagation, which estimates the impact of features on a DNN. They demonstrate that comparable accuracy can be obtained for image processing using federated learning, but higher levels of differential privacy correspond to lower accuracy [80]. Cao *et al.* also employ federated learning for data privacy, developing a method for processing data traffic through efficient agent selection; this ensures privacy and efficient communications on mobile edge computing devices [90].

Additional future considerations. Despite current research, data privacy is still a major challenge in V2V communications. Some might argue that consumers should have the option to opt in or out of sharing entirely, a consideration of current debate over mobile devices such as smartphones. Either way, as tracking and data collection continue to become more prevalent in our lives, privacy is undoubtedly a major concern in the minds of consumers. For widespread adoption of vehicular communications to occur, personal privacy issues must be addressed.

VIII. Training V2V-enabled ML Algorithms in Practice

Now that we have presented the considerations for improving ML using V2V communications, how would a researcher develop such a model in practice? In this section, we provide sources of data and simulation tools for developing and training V2V-communication enabled ML models.

Data Sources. In general, ML algorithms require training on large quantities of data related to the problem domain in order to be effective. This is especially true for vehicular communication between AVs. High safety thresholds, coupled with a highly dynamic environment for transceiver nodes, mean that V2X applications must rely on vast datasets to achieve required performance quality.

Broadly, an autonomous vehicle system equipped with V2X communication can be classified into three blocks: Perception, Maneuvering, and Communication [3, 4]. Here, based on these three system blocks, we outline several important sources of data that have been used to train ML algorithms for AVs and that will be useful to any researchers seeking to improve these algorithms. These are listed in Table VI.

Sensor data. Firstly, current AV research often focuses on processing sensor inputs from the AV (e.g. GPS, LiDAR, camera). These sensors provide the positions of obstacles and neighboring vehicles relative to the *ego vehicle*, or the vehicle which contains the sensors. GPS provides a location in non-Euclidean format, while LiDAR and cameras provide relative locations. The KITTI Vision Benchmark Suite is one of the earliest datasets for such a purpose. It consists of images, 3D GPS data, and point clouds - collections of 3D points representing the physical world [161]. Point clouds are gathered using LiDAR, which detects the location and distance of physical objects using lasers. In the past, KITTI has commonly been used for testing ML algorithms for vision tasks performed by AVs such as object detection. Other datasets featuring image and point cloud data for self-driving vehicle research include the Cityscapes Dataset [162], the Baidu ApolloScape dataset [163], and the Honda Research Institute Driving Dataset [164]. More recently, Waymo has

TABLE VI
DATASETS FOR EVALUATING ML ALGORITHMS AND V2X COMMUNICATION IN AVS

Application	Data Source	Purpose	Year	Source
Autonomous Driving	KITTI Vision Benchmark Suite	Camera and LiDAR data	2013	[161]
	Cityscapes Dataset		2016	[162]
	Baidu ApolloScape Dataset		2018	[163]
	Honda Research Institute Driving Dataset		2018	[164]
	Waymo Open Dataset		2020	[165]
Traffic	SUMO	Traffic simulator	2018	[166]
	CARLO		2017	[167]
	MATSim		2016	[168]
	OpenDS		2014	[169]
	PTV Vissim		2011	[170]
	Q-Traffic	Traffic data and auxiliary information	2018	[171]
V2V Communication Simulation Software	Veins	V2V communication and traffic simulator	2011	[172]
	iTETRIS		2013	[173]
	Eclipse MOSAIC		2011	[174]
	NetSim		2008	[175]
	MATLAB Vanet Toolbox		2019	[176]
5G Communication Datasets	Lumos5G	Urban mmWve 5G service measurements	2020	[177]
	CRAWDAD	General wireless communications data	2021	[178]
	ETSI ITS-G5 DSRC	Dedicated short-range communications	2019	[179]
	DSRC Vehicle Communications	Dedicated short-range communications with cyberattacks	2016	[180]
	Warrigal Dataset	Wireless ad-hoc data between industrial vehicles	2014	[181]
Other	ScanNet	Annotated 3D indoor scene point clouds	2017	[182]
	ModelNet	Large scale 3D image dataset	2015	[183]
	Starcraft II Learning Environment	Interface to Starcraft for multi-agent learning	2017	[184]

published an open-access dataset of LiDAR and camera data that is “15x more diverse than the largest camera + LiDAR dataset available” and will allow researchers to develop effective solutions to self-driving problems [165]. Using these datasets, researchers can develop solutions to computer vision problems in AVs and allow them to make driving decisions using ML.

Traffic simulators. Researchers may wish to examine how well V2V communication in AVs can help reduce road traffic. Traffic datasets and simulators also allow for an investigation of deep reinforcement learning specifically for collaborative traffic. For traffic models, the traffic simulator SUMO is frequently used for modeling how different autonomous driving techniques can reduce congestion [166]. CARLA is another commonly-used traffic simulation software as well [167]. Other traffic simulation software tools include MATSim [168], OpenDS [169], and PTV Vissim [170]. Similarly, Q-Traffic represents a large dataset from Baidu for building and testing traffic models [171].

Communication simulators. Simulations are also important tools for testing V2V communications because deploying such technologies in real-world field tests may be expensive and time-consuming [185]. There are three major software tools for V2V communications that have been in use over the past decade: Veins, which is based on SUMO and OMNeT++ (a network simulator) [172]; iTETRIS, which also uses SUMO and allows a wide variety of traffic, communications, and facilities specifications [173]; and Eclipse MOSAIC, which is an open-source version of previous software, VSimRTI, that combines multiple traffic and communication simulators including SUMO, PHABMACS, ns-3, OMNeT++, and SNS [174]. Other, more recent simulation software that has been developed for evaluating V2V communication in autonomous driving include NetSim [175] and the MATLAB VANET Toolbox [176].

Communication data. Raw datasets are also available for training ML algorithms for supporting 5G V2V communication. For 5G mmWave communications, Lumos5G provides a set of mmWave 5G service measurements in a large U.S. city [177]. Similarly, CRAWDAD is an established academic project seeking to compile datasets of wireless communications, including 5G [178]. Datasets specific to vehicular communication are available as well. DSRC data is provided in [179]. This dataset represents communications between onboard units and roadside units collected from driving a vehicle on the FLOURISH test track in the UK. A slightly older dataset for DSRC is provided in [180]. This includes DSRC communications between onboard units and roadside units and is accessible through the UCI ML Repository. It features information on cyberattack anomalies in the communication, making it useful for training ML algorithms for security purposes and anomaly detection. Furthermore, the Warrigal Dataset is presented in [181]; it contains wireless ad hoc data between trucks and four-wheel-drive vehicles in an industrial setting and has been used for intelligent transportation studies, making it potentially useful for V2V application testing.

Large-scale ML training data. Finally, different yet related datasets can be used for testing ML algorithms related to AV tasks as well. AVs often must analyze and make decisions based on point clouds. For point cloud processing tasks, ScanNet is an annotated set of 3D point clouds that represent indoor scenes [182]. In a similar vein, ModelNet provides a large-scale 3D image dataset for training deep learning models for image processing tasks [183]. For tasks involving collaboration between vehicles using V2V communications, multi-agent learning algorithms are often employed. The Starcraft II Learning Environment provides an open-source interface to the game of Starcraft [184] - this environment is frequently used for testing the performance of deep multi-agent reinforcement learning models. All of these datasets can be useful in building models to address various tasks in autonomous driving systems.

IX. Discussion and Conclusions

As we have seen, V2V communications have the potential to improve ML for autonomous driving tasks, but there is still a great deal of research necessary to achieve this goal in practice. While real-world implementations of V2V communications have improved autonomous driving performance, as in Jung *et al.* or Miuicic *et al.* [186, 114], most current research consists of simulation studies. As government standards for V2V communications improve, manufacturers will be more equipped to deploy V2V communications and rely on them for safety purposes [114]. Until then, researchers must continue to expand the theoretical foundations of collaborative ML algorithms.

Although current research explores possible solutions for a multitude of autonomous driving and communication problems, there are still many areas of potential yet to be addressed. For example, ML has not yet been employed for cooperative parking tasks [148]. In addition, security in autonomous driving systems is a crucial topic, one that requires much more research to confront the many types of cyber-attacks specific to vehicular communication [155]. The areas discussed in this paper have great potential for expansion, which we expound upon as follows.

Theoretical foundations of distributed ML. As evidenced by challenges in [124, 125], collaborative driving is an incredibly complex problem, especially for cases such as coordinating a set of vehicles to drive in a manner that maximizes safety while minimizing traffic. Addressing the complexity of V2V challenges may require advances in the underlying learning algorithms themselves. For example, deep multi-agent reinforcement learning appears to hold promise for enabling and leveraging V2V communications for a variety of more difficult tasks, such as collaborative driving. However, such methods still require methodological improvements to guarantee convergence for complex real-time optimization problems.

Similarly, federated learning can reduce latency and ensure data privacy, but this method has traditionally relied on the assumption of independent and identically distributed random variables. This assumption may not hold true, as every vehicle can drive on different routes depending on the daily behavior of its user. Therefore, research into the theoretical foundations of federated learning is necessary to prove such algorithms will converge.

Preventing adversarial attacks. Similarly, data fusion is an essential technique for allowing V2V communication to improve performance in ML. However, data fusion is currently susceptible to adversarial attacks and data poisoning. In current frameworks, it would be too easy for bad actors to supply faulty data to AVs and influence poor decisions. Combining data sources from different vehicles is an essential first step for using V2V communications for collaborative ML. Therefore, more secure data fusion algorithms would be highly beneficial, allowing vehicular ML algorithms to incorporate a wider variety of data sources.

Collaborative security. Along the same lines, security in AVs is underdeveloped. While ML algorithms have been proposed to detect anomalies in individual security tasks, other issues besides anomaly detection also must be addressed. For example, federated learning can help ensure data privacy across virtually any task that requires ML. Edge computing can also support security efforts as well. Furthermore, if multiple AVs could also incorporate collaboration on security tasks like they can on perception and driving tasks, it would be much easier for a vehicular network to prevent interference by malicious actors.

Incorporating V2V communications into fully autonomous systems. Finally, much research focuses on using ML for specific autonomous driving or V2V tasks but ideally, for implementations such as in [186], a complete V2V-enabled autonomous driving system would be necessary to develop. Systems, architectures, and design guidelines have been proposed [82, 100, 119] but more research is necessary to examine how well such systems perform and how they can be improved. It is also important to incorporate an overarching cybersecurity framework to address potential weaknesses in vehicular communication systems, ensuring safe tests can be conducted. Safe driving and communications are necessary for systems to be implemented and tested in practice.

Open Questions. The information in this survey paper and the identified areas of potential pose potential questions to be explored by future research. These include the following:

- What is the best way to ensure that the data transmitted in 5G V2V communications is truly useful? How can we ensure that messages arrive fast enough to inform an AV's decision-making and that the correct information can be incorporated into the autonomous control system?
- What are valid assumptions regarding AV sensor data in a dynamic vehicular network environment? How can we prove that optimization algorithms such as DMARL or FL will converge for problems in autonomous driving?
- Is it possible to coordinate the driving movements of a large number of AVs to minimize traffic while preventing collisions or safety risks? What sort of computational resources or techniques will be necessary to accomplish this feat?
- How can ML models detect and avoid adversarial attacks and data poisoning when fusing data from other vehicles?
- How can vehicles work together to solve security problems using 5G V2V communications while ensuring that such communications themselves are secure?
- How can V2V communication systems be integrated into the autonomous vehicle as a whole? How can we run practical tests in the real world to ensure that these systems work?

Answering these questions will be necessary to advance research in ML methods for V2V and V2X communications. Allowing AVs to communicate useful data from onboard sensors should ensure safe and efficient driving. In turn, meeting safety and efficiency standards will result in more widespread adoption and utilization of autonomous driving systems and vehicular communications in the transportation industry.

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