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Machine Learning and 5G Network Communication for Internet of Vehicles

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Abstract

The technology known as machine learning (ML) is widely used in the analysis of large amounts of data in Internet of Vehicles (IoV) networks. Enabling intelligent decision-making and forecasting with machine learning (ML) is essential for enhancing network performance and addressing congestion problems. The purpose of this review is to clarify how machine learning and 5G network communication interact in the IoV. In the IoV, machine learning (ML) is widely used in research spanning communication network levels, network management, data flow, and site forecasting. Intelligent systems with the capacity for parallel processing, energy efficiency for signal/image processing, and wireless communications can be designed to satisfy the unique requirements of Internet of Vehicles (IoV) networks by utilizing ML techniques and parallel computing. Investigating resource allocation and management strategies is essential to achieving optimal network performance and efficiency, especially given the exponential rise of 5G technologies. One of the biggest issues affecting network performance is managing in-car communication networks and allocating and managing resources. The large volumes of data that must be transferred from various sources throughout the network are the primary cause of these difficulties. Data-driven machine learning (ML) methods have become a feasible means of achieving optimal performance at a reasonable computing complexity. This study examines some of the machine learning algorithms that have found widespread use in the Internet of Vehicles (IoV), specifically focusing on their reinforcement and processes. The difficulties with cloud computing, resource management, and allocation in Internet of Vehicles applications are also covered. In order to enhance IoV resource allocation and management, we review 80 papers which evaluate prior research on the fifth-generation vehicle network architecture as well as machine learning applications from reliable sources, including Google Scholar, Springer, and Elsevier. It also discusses the intelligence applications that could transform the Internet's mode of operation through the use of sixth-generation networks, which are anticipated to be available shortly.

Keywords: Internet of Vehicle, 5G Networks, Machine learning, Mobile network, Communication, Security

I. INTRODUCTION

The rapid growth of computer systems and intelligent transportation systems (ITS) has made it possible to conduct novel, comfortable, and effective scientific studies in smart traffic safety. In many different research domains, AI turned out to be extensively employed to upgrade conventional data-directed methodologies [1]. The Vehicle-to-Everything (V2X) system, which is AI-based, gathers data from a variety of sources, including cars, trains, buses, and other vehicles, to improve driver awareness and estimate the likelihood of mishaps. This progress has made it possible to understand intelligent driving, which was based on the idea of imitating real-world driving behavior while preventing human error and offering drivers pleasurable safety. Numerous services have been established as a legacy of self-based car equipment to the IoV, from managing crowd and light transportation to traffic modification [2]. The goal of IoV is to alter how environments, roadside stations, onboard stations, and automobiles interact in order to transfer multimedia and data between different networks. The adoption and construction of the human-vehicle-roadside onboard IoT are the driving forces behind IoV. Connected services across many networks and car models.

Many AI applications are made possible by machine learning (ML) [3]. RL, SL, and unsupervised learning are ML approaches. Training in the unsupervised machine learning scheme requires untagged data. It looks for a suitable way to represent untagged data. On the other hand, supervised learning involves learning from a set of labelled data. Regression and classification algorithms are used in supervised learning to train discrete and continuous data for decision-making and prediction. $Reinforcement\ learning\ (RL)$ studies the behavior of the learning agent from the constant reward in order to take use of the concept of cumulative rewards. $Markov\ Decision\ Process\ (MDP)$ is one kind of reinforcement learning [2]. This plan is an ideal method for addressing numerous research problems related to automotive networks, like cooperative optimization of oil consumption within a certain region, optimum route prediction for electric vehicles, and reducing traffic jams. This paper presents a basic overview of machine learning (ML), one of the AI approaches. It talks about how it could be used in a few different IoV-related contexts [4]. This work makes a contribution considering the importance of AI in IoV, since most of its applications use smart models. The most significant issues in IoV networks are those related to edge computing and caching, which call for clever optimization techniques. The problems associated with edge computing and caching include changing communication topology, resource allocation management, and channel conditions. Artificial intelligence is in charge of the virtual cloud infrastructure on a different layer of the Internet of Virtualized Things network architecture. The AI layer functions as the brain of information management. DNN-based machine learning approaches are intended to make predictions based on the actions that IoV resources have learned. In order to offload mobile computing edge choices based on ML methods for vehicular interaction on the IoV, this study has conducted an analytical simulation and critical assessment. We have analyzed a conventional IoV network design with one $IoV\ Edge - Computing\ (IoVEC)$ along with a mobile user. These tasks are carried out by the gadget in a time-based flow [5]. The offloading choice method in the task flow is carried out as an MDP using our analytical model. The optimization object divides the reward for each time slot by reducing the weighted average of power use and offloading delay.

The 5G network supplies the fundamental framework for creating a smart IoV environment. In order to attain extraordinary performance, the vehicle network capabilities are pushed. The Internet of Everything (IoE) [6] can now evolve thanks to 5G technology, which offers huge connectivity, lower power consumption, and quicker speeds. This can enhance all aspects of life and aid in digitization. The implementation of 5G networks for applications in industry and the combination of AI with other technologies, such as the use of edge computing, visual and detecting technology, and augmented and virtual reality, will lead to high technology evolution [7, 8]. 5G communications guarantee the improvement of apps that function more intelligently and efficiently inside various integrated technology types.

More dependable communication at very high speeds and minimal latency is made possible by 5G networks. The creation and utilization of 5G networks are made possible by technologies like network function virtualization (NFV) and software-defined networking (SDN). The

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integration of new services that are open, adaptable, and programmable is made possible by the usage of SDN in 5G networks. This will guarantee a high-performance platform for 5G-based autonomous vehicles [9]. Control and data are kept apart in SDN-based 5G networks to provide centralized, effective resource management with safe distribution. For the 5G vehicle network architecture, SDN offers variable resource allocation and communication management, enabling network settings to be safer and more private while also enhancing performance [10].

II. 5G WIRELESS MOBILE NETWORK DOMAIN

The taxonomy made it abundantly evident that Machine learning and deep learning architectures were used to solve issues in several 5G domains. Applications in this sector include mobile networks, 5G-enabled vehicle networks, resource management, signalling, mobility, energy, and cyber security defensive systems. The taxonomy demonstrated how much attention the researchers paid to various facets of resource management and mobile networks.

- ***Resource Management***

The uses of ML and DL algorithms for resource allocation in 5G technology are covered in this section. A DeepCog based on 3D CNN was created by [11] to handle resources in 5G mobile networks. In 5G technology, the network infrastructure is divided into segments. It is planned for each slice in the DeepCog to have a distinct set of resources assigned to it. DeepCog is found to be quite effective when evaluated in an actual environment. In 5G mobile wireless networks, deep learning for determining the allocation of cooperative resources based on channel conditions was first presented by [12]. The study generated CNN with network data and allocated resources intended for optimization. The produced CNN, rather than the conventional resource, can assist in optimizing the full-scale channel data to optimize usage, particularly in a dynamic transmit environment. It is discovered that the technique works well for cutting down on optimization complexity, speeding up computing, and delivering good results.

ML and DL for end-to-end slicing and service level agreement-based resource allocation for 5G network stability was proposed by [13]. The traffic slices are predicted by the controlled recurrent neural network, while the DDNN is used at every virtual network to assess the resources needed. A network slicing method was presented by to effectively slice and manage core and radio access network facilities[14]. The network resources are then managed by GAN, which is found to operate more efficiently in terms of latency and bandwidth. [15] Investigated 5G-enabled TV multimedia allocation and suggested a deep learning system. User bandwidth and power resource allocation are linked with DRL. Subsequently, traffic multicast services are constructed using the LSTM, resulting in increased energy efficiency.

In order to satisfy service requirements in 5G, [16] introduced DRL for radio resource allocation that was independent of slice count. The use of 5G-V2X based on DQN for platooning vehicle station allocation optimization was suggested by [17]. It is making an effort to offer a solution to the base station allocation issue. In a 5G network-enabled smart grid, [18] suggested using RL for the dynamic arrangement of the $network\ slice\ resources$ to enhance the QoS. During the resource allocation operation, the algorithm can quickly adjust the network's demand. In order to reserve resources for $ultra-reliable\ low-$

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$latency\ communication$ in a $5G\ network$, [19] proposed RL. It is come to know that in terms of resource usage and the f packet drop probability, RL outperforms the baseline approach.

$DQN\ uplink/downlink$ resource allocation for 5G miscellaneous networks was proposed by [20]. The features of the complex network information were obtained by means of a deep belief network. Using a Q-value predicated on the DQN with the reply, the reward technique modifies the time separation duplex up/downlink ratio. The recommended DQN-based time division duplex performs better than the resource allocation strategy based on the traditional time division duplex when network performance is measured in terms of capacity and packet loss rate. The use of adaptive DQN by [21] for 5G service operation chaining mapping methods that are available on demand. In the proposed approach, an agent makes decisions that meet user needs by utilizing a complicatedness $heuristic$ response function linkage mapping mechanism. After taking the experience into account, a plan is found to efficiently schedule two heuristics in order to optimize all system resources.

- $\boldsymbol{Cyber\ security\ Defense\ system}$

Protecting the 5G-wireless MN from cyber attacks is necessary [22]. Thus, in order to address the security challenges, mechanisms and protocols serving as the foundation for the fortification of the 5G-network are required [23]. According to [24], providing intelligent systems with a security breach detection method that is both effective and efficient is crucial. [24] A deep learning anomaly detection system for network flows was suggested in order to find assaults in 5G mobile wireless networks efficiently and successfully. Real-time network traffic flow inspection is performed using both the DBN and the $LSTM$-based incongruity finding technique. The structure's initial level quickly carries out the DBN on every RAN. It then looks for unusual symptoms in the $network\ traffic\ flow$. The LSTM used the collected anomalous symptoms as I/O to identify a pattern of cyberattacks. With more thorough and broad results, the work has been expanded in [22]. By incorporating $mobile\ edge\ computing\ (MEC)$ design in the administration of $5G\ wireless$ networks detect anomalies unconventionally in real-time according to guidelines, [23] expanded on the work in [22]. The policies facilitate the effectual, effective, and vigorous control of the computational facility utilized in the traffic flow analysis of 5G networks for peculiarity identification. Adaboosted ensemble LSTM was proposed by [25] for the purpose of detecting abnormalities in 5G radio access networks. The 5G random access network uses the suggested ensemble approach to find abnormalities. Adaboosted ensemble LSTM can reliably and quickly identify anomalies in random access networks.

In order to identify and remove security threads prior to assaulting the 5G core wireless network, [26] employed DDNN. Network slices can be sold as a service under the suggested paradigm, allowing multiple services to be hosted on a dependable and highly secure single infrastructure. CNN was proposed by [27] for 5G mobile wireless network anomaly detection. It is discovered that the CNN algorithm works well for intrusion detection while minimizing the effects of latency. [28] suggested using CNN to create a framework for detecting distributed denial-of-service attacks on 5G networks, which are caused by malicious botnets controlling devices. The cyber-physical system is the primary target of these attacks. It is discovered that the framework detects attacks with an accuracy of more than 90%.

- ***Mobile Network***

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[29] created an intelligent offloading architecture that combines licensing spectrum and unlicensed spectrum channels predicated on $DRL\, 5G - enabled$ vehicle systems. The development of a distributed DRL-based strategy aims to enhance the communication between automobiles and macro cells greatly. It was discovered to diminish unloading costs and uphold user reaction time constraints concurrently. Finally, the method significantly reduces distributed offloading traffic. The Deep Q-Learning (DQN) technique was presented by [30] for beam selection using $5G\ MN - MIMO\ data$. The creation of e-channel accomplishment involves merging ray tracing simulators with vehicle traffic and things that symbolize the 5G environment. A channel and mobility model was created. Temporal CNN was proposed by [31] for millimetre wave outdoor locating in 5G mobile networks. Achieving baseline precision for $non - line - of - sight$ millimetre wave open-air sites, the temporal CNN retained moderate bandwidth, a single anchor, and an average error of 1.78 meters. Deep reinforcement learning (DRL) was used by [32] to create a caching system for 5G and beyond MN. The deep reinforcement learning caching technique maximizes the caching resource usefulness according to numerical data. The 5G cloud random usage network load-balancer based on DRL for generic online education was proposed by [33]. Next, load balancing in the 5G virtual randomization network is accomplished by implementing the recommended approach. Cache misses and communication load are found to be reduced with little system overhead.

$Deep\ Autoencoder\ sparse\ code\ multiple\ access\ (Deep - SCMA)$ was introduced by [32] for the 5G mobile wireless network. The bit error rate is reduced by the Deep-SCMA codebook by combining adaptive construction with deep Autoencoder-based interpretation and encoding. The results showed that the Deeper SCMA system performed better with regard to of bit error rates and processing speed than the conventional technique. CNN-LSTM hybrid technology was employed by [34] to predict information about the channel status in a 5G cellular network. Two scenarios were conducted inside and two outside to assess the suggested plan. The results demonstrated that in a very short length of time for convergence, the CNN-LSTM can foresee the channel state data in a 5G system with a mean variation ratio between 2.650% and 3.457%.

- ***Caching***

[35] employed MEC to enhance $caching$ in $5G\ mobile\ networks$ using an $LSTM$ structure, which speeds up $smart - based\ intelligent\ caching$ as opposed to the widely utilized occurrence and time-based caching for swapping out approaches and fostering base station cooperation. For each base station to make a judgment according to the intelligent cache, the LSTM intelligent-based cache framework recognizes the unique pattern request. Transmission latency is lowered by at least 14%, and backhaul data traffic can be saved by up to 23% thanks to the clever LSTM-based cache architecture. In order to execute the optimal policy in an online way, [36] presented a DRL-based caching scheme that uses Q-learning. This allows the base station's cache management unit to observe and acclimate to modifications in the environment. The introduction of the Q-learning linear function estimate gives rapid computing time, lowers complexity, and requires less memory in order to incorporate the approach with scalability. The Stacked Sparse Autoencoder (SSAE) caching approach was proposed by [37] for the 5G mobile wireless network's Evolved Packet Core. The creation of the virtual distributed deep learning statement on SSAE makes use of the $network\ functions\ virtual\ (NFV)$ and $software - defined\ network\ (SDN)$. Afterwards, the SSAE forecasted the popularity of the content. In light of the expected result, the SDN regulator produces the reserving procedure, which is then synchronized to each store hub by means of the stream table for the technique

execution. It is found that the profound learning-based approach beats the standard methods with regards to store execution improvement.

- ***Other Domain***

GAN was utilized for precision farming by [38]. The 5G remote portable organization is planned to utilize the GAN-based picture investigation system. Accuracy cultivating may significantly benefit from the incorporation of 5G remote organization innovation, unscrewed ethereal vehicles, and smart calculations, as per a GAN-based automated elevated vehicle picture handling structure. It has been demonstrated the way that the clever structure can screen farming regions with drones that are associated with 5G and cameras, consequently limiting the requirement for human communication.[38] Presents different profound learning strategies across numerous 5G spaces. It shows the space, profound learning engineering, and related references for each plan. To streamline asset allotment, calculation offload, and reserving position,[39] formulated a DRL time scale that comprises of fast and slow courses of events educational experiences. Combined learning is utilized to prepare the DRL in a dispersed way while keeping up with the security of edge gadget information. The trial shows that the recommended technique decreases assembly time by over 30%.

III. COMMUNICATION TYPES OF IoV

Five different communication modes have emerged from the heterogeneous communicant nodes of the Internet of Vehicles (IoV) network. The first two, V2V and V2R, use technologies for data dissemination, such as dedicated short-range communication (DSRC) or as wireless access in vehicular environments (WAVE). The third mode is V2I correspondence, which depends on both cell organization and Wi-Fi advances. The last IoV correspondence modes are V2S and V2P gadgets (or walker - V2P-), which utilize short-range media like ZigBee, Close to Handle Correspondence (NFC), or Bluetooth advancements. The following is a clarification of every one of these IoV correspondence modes:

- ***Vehicle to vehicle***

Vehicle-to-vehicle (V2V) communication is a transmission mechanism that enables single- or multi-hop vehicle-to-vehicle communication. Multihops are better for V2V communication since they prolong network lifetime and prevent data loss [40]. Drivers would receive important information and a crash warning via a 30 V2V connection. The driver maintains control of the car at all times and will get warnings about potential threats through a visual display, vibration in the seat, or tone. These alerts can assist drivers in taking swift action to avert possible collisions. V2V uses the IEEE 802.11 protocol's wireless communications DSRC.

- ***Vehicle to infrastructure***

The communication between a vehicle and infrastructures that are permanently positioned on a road is known as vehicle-to-infrastructure (V2I) mode. These infrastructures are often base stations (BSs) or access points (APs) that are used to send road messages over cellular networks such as GSM, 3G, or LTE/4G. In order to increase road safety or provide road services, these messages may be delivered by the government, public relations firms, or local cars. Other IoV nodes may then collect them. DSRC for communications approved under IEEE 802.11 protocol

- ***Vehicle to roadside units***

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Vehicle-to-vehicle (V2R) unit communications are used to collect data on cars or newly occurring road events and relay this data to other vehicles in the traffic area or to handle these events via IEEE 802.11p connection. For example, the roadside unit (RSU) can identify that an ambulance is passing in front of traffic lights. The RSU then modifies the traffic signals to permit the ambulance to pass and notifies other IoV nodes about this type of emergency vehicle.

- ***Vehicle to personal devices***

Vehicle-to-pedestrian, or V2P, technology enables a vehicle to send emergency or traffic messages to people's devices (such as smartphones, PCs, tablets, smartwatches, etc.) to notify them of an occurrence or issue, such as a vehicle breakdown, request Assistance, or warn other vehicles or pedestrians. Short-range communication technologies like NFC, CarPlay, ZigBee, and others facilitate connectivity between personal devices and vehicles.

IV. MACHINE LEARNING ALGORITHMS IN THE IoV NETWORK

Several models, classifiers, and training techniques from machine learning are frequently applied to prediction issues and intelligent management. Reinforcement learning will offer guiding behaviour in Internet of Vehicles applications to support scalability and resilience [41]. In IoV networks, it can provide route optimization or path selection. When used as an operation and maintenance method, machine learning can guarantee throughput maximization and delay reduction [42]. IoV network performance will be enhanced by ML and SDN working together to provide reliable and excellent routing services. In order to achieve higher usage, they can guarantee the best routing policy adaption based on sensing and learning from the IoV environment [43]. When it comes to IoV network security, ML combined with SDN offers some special benefits for security solution deployment. In order to create ML software communication with the SDN data plane and send statistical results to the application layer upon vehicle requests, it will be convenient to have centralized management over security issues on the software layer with access to APIs.
Mechanization and association assume a significant part in self-driving highlights of mental Web of Vehicles (CIoV) applications, for example, computerized driving, which ought to have sufficient knowledge to bring down car crashes. CIoV mitigates security and protection worries in transportation frameworks by empowering cloud-based AI. ML offers vital administrations for a few capability levels in the CIoV cognizance and control layer, for example, driving way of behaving, wellbeing checking, example and feeling examination, and organization asset distribution and improvement [43]. Profound learning plans offer smart decision-production to evaluate the pivotal, compelling impact likelihood components and risk of expected mishaps in the IoV, subsequently working on driving security and proficiency in the transportation framework. For impact expectation and mishap guaging, an assortment of profound learning draws near, like fluffy rationale, brain organizations, and GA, can be utilized.

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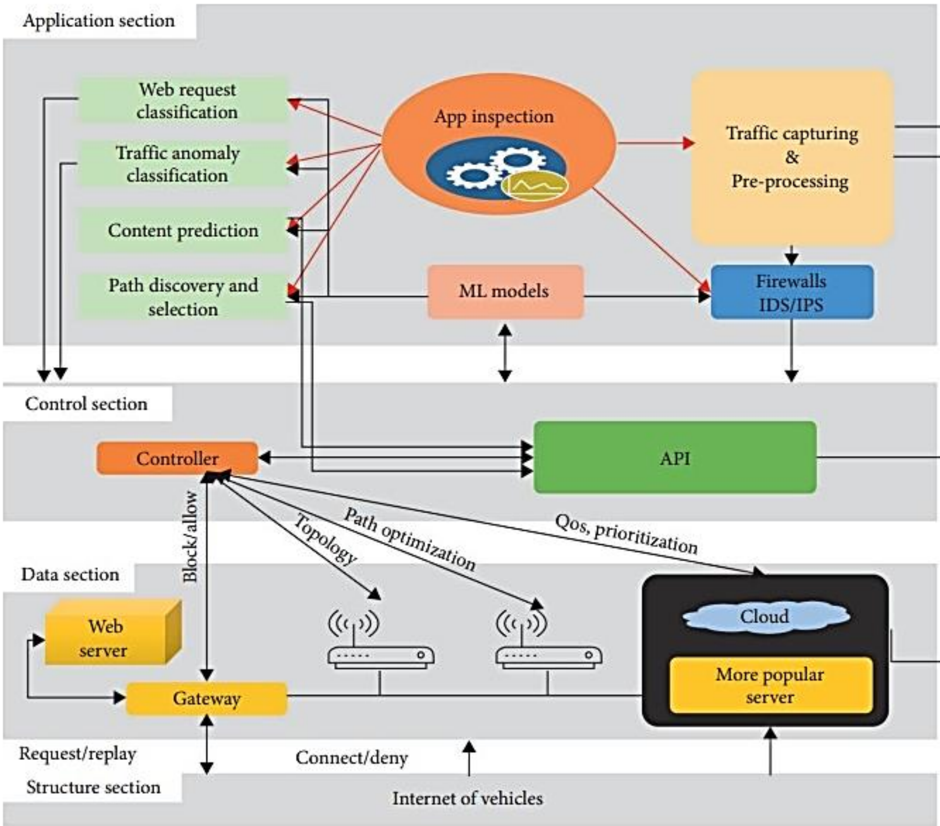

Figure 1: Function of ML in IoV Network [43]

4.1 ML-based Edge Caching Mechanism for IoV

The cache and computing architecture in IoV determines both cost-effectiveness and operational quality. Ensuring efficient QoS for applications can be achieved through the placement of edge caching and computing offloading at the vehicles and RSUs [44]. Machine learning offers solutions to caching, processing, and communications issues for the Internet of Vehicles. In IoV, edge caching can be implemented using a variety of ML methods. In supervised learning, it offers reasonably accurate caching judgments, IoV traffic level categorization prediction, and content demand. Vehicle behaviour and data request history can be used to cluster vehicles into distinct groups for the purpose of applying unsupervised learning to the edge caching design. Depending on the interests or social connections of the entire vehicle group, the ML-based clustering algorithm can forecast the data needed [45].

The parameters of computing and caching for resource allocation will be optimized through the application of deep Q-learning. From the gathered status of MEC and RSU servers, along with each vehicle's mobility, channel information, cache contents, and computing, deep Q-learning will identify the best course of action. The vehicles receive this action. To fulfil requests and calculate offloading jobs for the Internet of Vehicles, Deep Q-learning will choose the optimal set of caching activities for RSU, MEC, and vehicles. There are difficulties in processing and analyzing data when integrating machine learning with edge caching [45]. Diffusion and high data density present difficulties for the process of training and learning. Furthermore, low processing power can alter high-dimensional data, which needs to be more accurate to make buffering decisions. It demands an efficient learning strategy for enormous high-dimensional data that is established to give an accurate estimation of the buffered information at the IoV network edge in order to firmly cooperate with ML at the edge to boost the edge's smart tasks. Furthermore, the employment of machine learning (ML) techniques in

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Internet of Vehicles (IoV) applications would extract a great deal of sensitive and important data, and any information leakage could raise major issues with confidentiality, security, and privacy [45]. In order to address these issues, an edge-caching system needs to be built at several system levels, including transmission/collection, processing, information access, and storage capacity for edge networks and vehicles. It also needs to be protected by security and privacy-preserving systems.

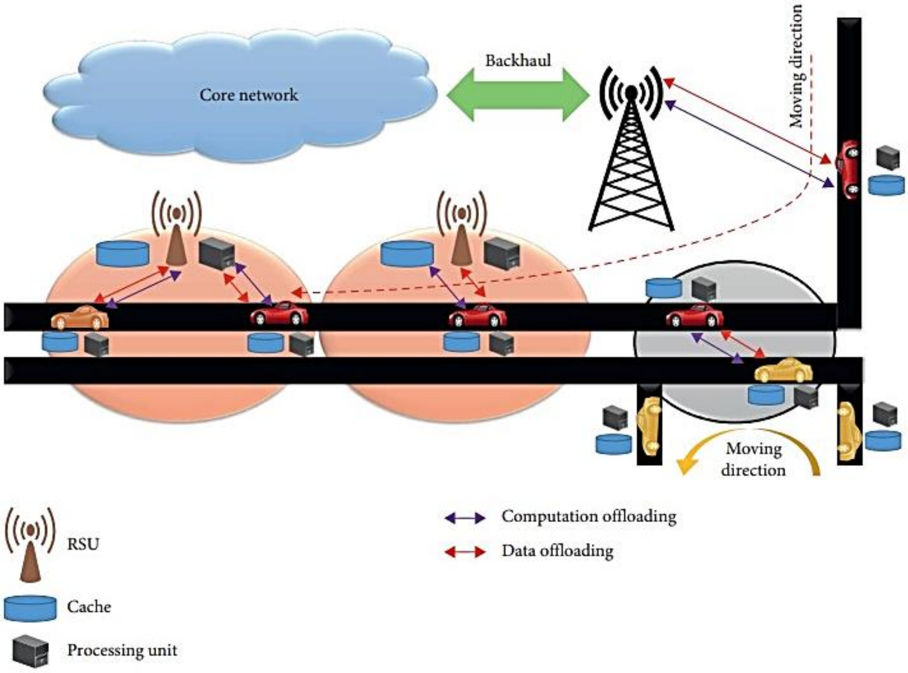

Figure 2: IoV Computational Scenario and Mobility-aware caching [43]

4.2 ML Applications in IoV

Machine learning is useful for several Internet of Vehicles (IoV) applications related to risky actions and emergent message sending for road safety. Moreover, ML provides innovative, ingenious solutions for IoV and entertainment services. An alternative to traditional decision-making methods is machine learning (ML) technology, which is used in data mining, pattern recognition, processing, and cognitive computing. It can lower the total energy consumption of computer facilities and vehicles while meeting the traffic offloading delay restriction. This will create new potential for intelligent IoV networks in areas like autonomous driving, smart transportation, and driver safety.

- ***Intelligent Autonomous Driving***

In applications involving intelligent driving, machine learning is essential because it helps cars sense and estimate how best to operate their driving systems. Because ML makes cars self-automated, fewer traffic accidents will occur, improving society [46]. Self-driving cars and the Internet of vehicles are generally closely related. An intelligent driving system will be produced by converging the IoTs, ML, and smart computing. Thanks to machine learning algorithms used in self-driving cars, IoV can anticipate probable changes in the surrounding driving environment and perform numerous tasks, such as object detection and identification, in addition to anticipating the location and movement of other vehicles [47]. The aforementioned tasks can be accomplished via a range of ML techniques. A localization technique for the creation of forecasting and feature selection frameworks for self-driving cars is provided by regression methods. Intelligent localization strategies like centroid-based and hierarchical can be modelled using clustering algorithms [47, 48]. Decision matrix algorithms will aid in finding, analyzing, and rating the effectiveness of links between sets of values and data in order to promote intelligent decision-making.

Deep learning for Driver safety and Assistance

Because road accident rates are rising and there is a critical need to reduce them, modern cars are equipped with sensors and connected to high-speed mobile communication networks [49]. Large volumes of data are gathered from automobile sensors and used in car safety analysis procedures. AI algorithms analyze the data in real-time for autonomous driving system applications in order to maximize safety by utilizing a variety of designs. It makes it possible to plan the road safety index and forecast variables like traffic flow, human behaviour, and street infrastructure. By using a deep, dense neural network, DL can forecast the real-time road safety index, which in turn can predict the description of road safety. Additionally, using image processing to predict road safety, machine learning (ML) aids in learning the relationship between visual entities and city attributes [50]. The road safety index can be predicted with high prediction accuracy by extracting the relationship between taken photos and estimated road safety using a variety of cross-domain parameters. The real-time estimation of the road safety index will improve vehicle safety.

V. SECURITY IN IoV

IoV applications fall into three primary areas, per [51]: applications for comfort, applications for safety, and applications for transport efficiency. However, a number of obstacles and problems, including heterogeneity, mobility, latency, network scale, and infrastructurelessness, need to improve the widespread implementation of IoV in smart cities [51]. Given that vehicular networks provide extra security vulnerabilities and privacy issues, the security of the Internet of Vehicles (IoV) is a major concern for smart cities [51-53]. [54] Proposes the creation and definition of privacy principles as a solution to the absence of privacy in the Internet of Things. This would help users understand what is and is not protected. The [54] recommends the creation of a privacy code of practice that outlines improper data management procedures in the Internet of Vehicles in addition to privacy regulations [54]. IoV uses access control and authentication measures to protect privacy. An authentication system, for example, was suggested by the [55] to secure vehicle communications in Internet of Vehicles contexts. Recently, IoV-SMAP, a message authentication mechanism, was introduced by [56].

IoV can leverage current security solutions for authentication. For instance, utilizing Radio Frequency Identification (RFID) technology [57] has suggested a cloud-based mutual authentication mechanism. Similarly, a method for secure data transfer and authentication based on blockchain technology has been presented by the [57]. To strengthen security in the Internet of Vehicles, authentication methods might be paired with other security measures. In order to address issues with authentication, non-repudiation, and anonymity, the [58] have presented an intelligent transportation system with a network security mechanism in an Internet of Vehicles environment. Cloud-based fog in the context of IoV IoV refers to mobile cloud computing. Vehicles serve as fog nodes in a multi-access edge-based vehicular fog computing architecture, as presented by [59]. The gateway selection module in the suggested design lowers communication costs by choosing appropriate fog nodes. For fog-based IoV, [60] suggested AKM-IoV, an authorized key management protocol.

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5.1 Advanced IoV applications

[61] " Mobile Edge Knowledge and Processing for the IoV" gives a layout of the edge data framework (EIS), which incorporates edge figuring, edge reserving, and edge simulated intelligence. These highlights will consider the advancement of a few creative and entrancing savvy IoV applications. Equipment stages, key plan concerns, and system are presented. Outlines of normal applications for keen vehicles incorporate confinement, planning, and edge-helped discernment. Applications for Vehicle-as-a-Client (VaaC) and Vehicle-as-a-Server (VaaS) for edge reserving, edge figuring, and edge computer based intelligence are studied.
Chen et al.'s article "Learning driving models from parallel end-to-end driving data set" investigates the successful utilization of genuine world and reproduced information to improve the abilities of equal start to finish independent driving, which utilizes perceptual information, (for example, pictures, point mists, and such) and other vehicle information, (for example, speed and route orders) as contributions to the model and results choice information (like guiding point) straightforwardly. In this article, an equal start to finish driving informational collection (PED) containing vehicle information, related mimicked world photographs, and genuine photos is presented. The aftereffects of the examinations show that PED are proficient and produce improved results. It is desirable over utilize the reenacted world information to prepare the driving model by first changing over the reproduced world picture into this present reality picture and afterward consolidating it with this present reality picture.

VI. IoV IN 5G NETWORK

IoV includes a number of definitions and concepts that have been well-covered in the literature. IoV is regarded as one of the IoT technologies associated with intelligent transportation technology (ITS), according to the Asia-Pacific Economic Cooperation (APEC) China group (2014), since it depends on the integration of the vehicle's mobile network as well as internal and external vehicle networks [62]. The following is how the writers described this idea: IoV, or infrastructure-to-vehicle, is a wireless communication system based on data transfer between multiple cars and V2X networks, where X refers to any object that is in a vehicle's path or on the road. According to, the Internet of Vehicles (IoV) is the combination of various factors, such as people, cars, and the environment, with a large smart network that provides a number of services as an application for roads and traffic management in big cities [63] [64]. They proceeded to say that the Web of Vehicles (IoV) expects to upgrade and diminish transportation costs, driver security, and traffic the board with high proficiency, as well as giving diversion applications and administrations, security data, and entertainment. The concept of IoV was first presented by [65] as a sign of the growth of VANET networks and the variety of uses that allow for passenger-vehicle communication. Additionally, it offers the chance for information to be shared between moving cars and the surroundings in order to improve driving economy and traffic safety. IoV is presented by [66] as a fusion of intelligence and network. Different communication technologies, including 4G / LTE and 5G, can be used by cars to communicate with their surroundings. Additionally, by utilizing enhancement technologies, processing and storage enhancements, cloud and fog computing capabilities, and several other smart technology advantages, a number of communication models, including vehicle-to-roadside (V2R), V2V, and V2I, can be configured.

- ***Complex networking***

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When multiple networks connect, such as 4 G and 5 G, there are issues with interoperability and defecting errors in the hierarchical separation structure. Furthermore, networking complexity will rise due to the unified resource scheduling issues brought on by the dynamic changes in cloud and virtual networks [67] [68].

- ***Diverse Service***

A full-scenario communication method involving man-to-man, man-to-machine, and machine-to-machine communications has progressively replaced the single man-to-man communication mode. Differentiated SLA needs, including high bandwidth, a large number of connections, ultra-high reliability, low latency, and related complex network administration, will arise from increasingly complex business situations.

- ***Personalized experience***

5G service experiences will typically be varied and individualized, with features including immersive experiences, real-time engagement, and subtle knowledge of emotions and intentions drawing on 5G network capabilities and plentiful business patterns. The experiment's network support will demolish the conventional model and face new difficulties. As a result, there will be a difference between advanced operations and conventional operations based on expert expertise due to the substantial hurdles presented by 5G. As a result, only 5G generation networks will be able to utilize automated and intelligent network functions. Artificial Intelligence (AI) technology offers innovative capabilities and efficient approaches to analyze large amounts of data. It also offers clever ways to manage resource operations in the 5G network and develop dynamic strategies [69]. Eventually, a network combining 5G, AI, and IoV will emerge as the intelligent center of the digital society, promoting the intelligent networking of everything reliant on cloud infrastructure. Built on cloud and service-based architecture, IoV-based 5G networks differ greatly at different network layers [69] [70]. With a centralized smart engine (SE) for centralized global strategy training and reasoning, the upper layer is more centralized and demands greater cross-domain analysis and scheduling capabilities. Examples of these capabilities include global cloud resource coordination and E2E slice orchestration and management. Intelligence upgrading of professional subnets or individual network pieces will be the focus of the lower layer toward the end. Introduce lite SE (LSE) to enhance the intelligence of subnets or sub-slice domains, including access, bearer, and core networks, through management strategies and devious activities [71].

Table 1: Overview of AI Techniques in Secure Vehicle-to-Everything Networks

References	Features	Security approaches	Challenges	Advantages
[72]	AI-based V2X automotive security framework	Security-Aware FlexRay Scheduling Engine (SAFE); Controller Area Network (CAN); Hardware	Cybersecurity in totally independent V2X	Catches sensing as well as communication layers' attacks

		Security Module (HSM); IDS.		
[73]	ML in fifth-generation (5G) IoV	Cloud Security Alliance (CSA); NSL-KDD data mining	Ensuring Quality of Service (QoS), performance, scalability, and cost-efficiency in secure dynamic networks for Vehicle-to-Everything (V2X) communication.	Security problems connected to software-defined perimeter, virtualization, and softwarization.
[74]	detection based on ML for secure V2X traffic	Basic safety messages (BSMs)	Recognize and notice the V2X location spoofing	Notices spoofing attacks in the V2X application layer
[75]	Cognitive security based on context-aware proactive security	physical layer security (PLS); Intelligent V2X security (IV2XS)	Determinate the best-suited class of security.	"Security decision-making based on the condition of vehicles' communication channels."
[76]	V2X traffic safety-based ML algorithms	MLP, RF misbehaving classifiers, Adaboost, MinMax	Secured decision for V2X traffic security	A transgression classifier for the vehicle data category

VII. 5G BASED IoV COMMUNICATION SYSTEM

The Internet of Vehicles (IoV) idea relates to the communications between vehicles and other objects within the transportation infrastructure. This type of communication is primarily based on Internet protocol, which allows information to be exchanged in a way that promotes efficiency and safety in transportation. The implementation of an IoV environment is contingent upon several factors [77]. These elements, which include environmental driving for energy economy, safety and emergency management, and intelligent traffic management, are regarded as a scenario approach in internet-connected car applications. AI technologies have recently offered practical ways to view massive IoV networks that employ a lot of cars, sensors, and computing with more effective communication capabilities [78]. Historically, in-car networks like GSM and UMTS—even the newest networks like LTE—have been the primary means of cellular connection. With significantly higher data capacity than 4G networks, fifth-generation (5G) wireless networks have recently emerged, enabling various devices to converse and exchange data more effectively [79]. The Internet of Vehicles (IoV) has grown

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rapidly because 5G technology offers very large bandwidth breadth and fast data interchange speed with low latency while maintaining low power. Certain of the current automobile network communication systems can be replaced or enhanced by 5G communication network technologies. One of the key components that would support the expansion of IoV services and applications is the new 5G, which is based on D2D terminal direct communication technology[80]. The idea of vehicle-to-vehicle (V2V) communication, which primarily depends on device-to-device (D2D) communication in a 5G cellular environment, is connected to the advantages of 5G communication. D2D communication expands communication applications, enhances user experience, and boosts spectral efficiency.

Long-term Evolution (LTE) technology is the key to solving this issue; however, it is unable to sustain regular V2V connections. Since D2D is a fundamental 5G network technology that allows data to be sent directly between devices, using infrastructure-assisted D2D communication technology can be a natural step toward achieving dependable and effective V2V communication. On the other hand, V2V communication in 5G networks can be achieved naturally by utilizing infrastructure-assisted D2D communication technologies.

- ***Transmission timeliness***

The V2V connection in IEEE802.11p experiences a transmission delay of roughly 10 ms. For V2V communication, this transmission delay is lowered to 1 ms while utilizing a 5G coverage network. However, the IEEE802.11p communication delay issue can be successfully resolved by 5G automobile network V2V communication transmission delays of up to 1 ms, ensuring prompt information reception.

- ***Transmission rate***

The data transfer rate of the 5G vehicle network will rise almost tenfold compared to IEEE802.11p to enable high-quality audio and video communications between the automobile and terminal equipment.

- ***Communication distance***

A 5 G vehicle network can cover up to 1000 meters for V2V communication using IEEE802.11p, with a quick connection time.

- ***High-speed mobility***

D2D can match the quicker vehicle communication requirements as a substitute for IEEE802.11p standard communication, as it supports vehicle speeds up to 350 km/h.

- ***Increase spectral efficiency***

There is a hop gain since data is sent directly between cars rather than via a cell network. Reusing resources within and across vehicles and cellular networks can increase gain. To improve network productivity and wireless spectrum efficiency, hop gain and resource reuse gain can be obtained.

VIII. FUTURE DIRECTIONS

The introduction of Internet of Vehicles (IoV)-focused communication frameworks has been facilitated by the introduction of fifth-generation (5G) wireless technology. Smart car networks are now required because of the widespread use of sophisticated mobile applications, especially those that use artificial intelligence (AI) technology. This has created previously unimaginable opportunities. In order to provide communication services that can meet future demands, businesses and academics are investigating the next generation of wireless communication systems, or 6G, in response to the quick development of 5G communications.

IX. DISTRIBUTIVE ANALYSIS

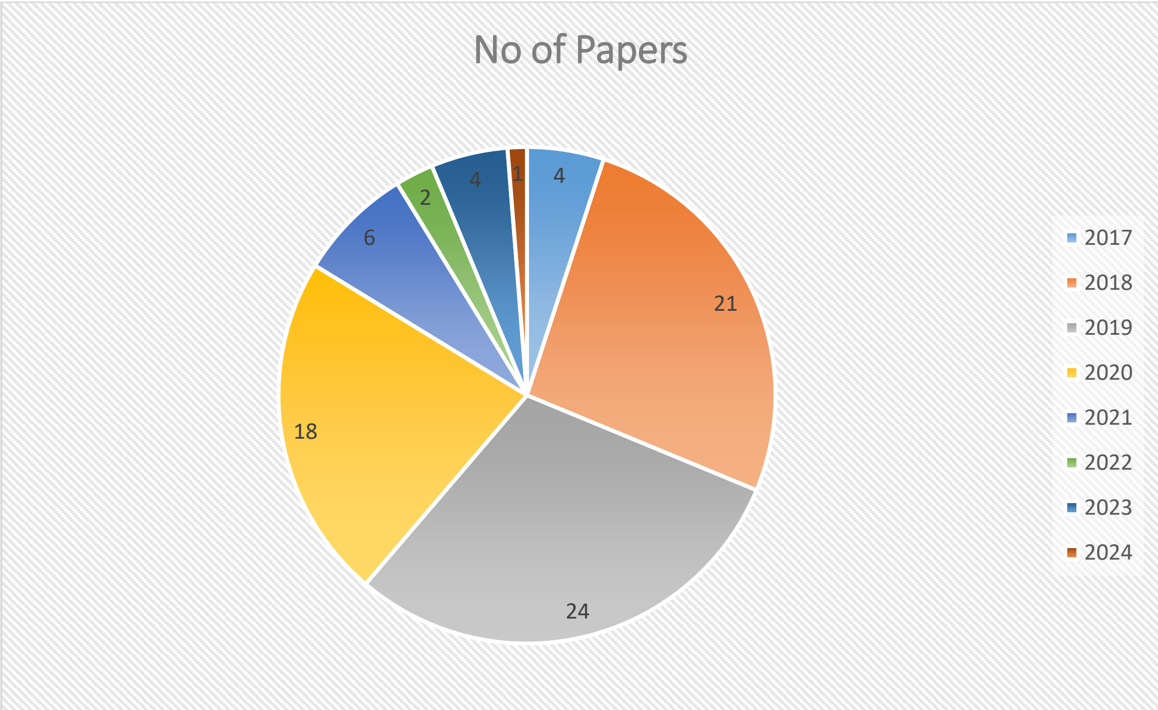

Figure 3: Distributive Analysis

As part of our research, we conducted a comprehensive review of 80 academic papers related to the application of Machine Learning and 5G Network communication for the Internet of Vehicles. The review was conducted over several years, starting with an analysis of four (4) papers in 2017, followed by an analysis of twenty-one (21) papers in 2018 and twenty-four (24) papers in 2019. In 2020, we evaluated eighteen (18) papers, followed by a review of six (6) articles in 2021. In 2022, we analyzed two (2) papers and reviewed an additional four (4) papers in 2023. Finally, we reviewed one (1) paper in 2024. Our analysis aimed to furnish a practical understanding of the role of Machine Learning and 5G Network communication in the development of the Internet of Vehicles. Through our review, we identified various trends and key areas of focus that have emerged in recent years. These findings deliver beneficial discernment for businesses and academics looking to leverage the power of Machine Learning and 5G Network communication in the evolution of the IoV.

Conclusion

ML is utilized in IoV networks to analyze massive data, allowing for smart forecasting and decision-making. It can alleviate congestion issues and enhance network performance. Research across communication network tiers, data flow, site forecasts, and network

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management can all benefit from machine learning. IoV network smart systems can be developed using parallel computing and machine learning techniques. With our work, intelligent systems for signal/image processing and wireless communications in the Internet of Vehicles (IoV) can be built with energy efficiency and parallel processing capabilities. Given how quickly 5G technologies are being used, it is critical to look into 5G resource allocation and management techniques in order to achieve a high degree of network efficiency and responsibility. The performance of in-vehicle communication networks is confronted with several significant issues, including resource allocation and management. The enormous amounts of data and information that must be transferred to and from a variety of sources via a network serve as a metaphor for the difficulties. Data-driven enabling machine learning (ML) techniques have recently been created to achieve optimal performance at a reasonable computing complexity. One of the most crucial artificial intelligence (AI) tools for controlling vehicle networks based on 5G networks is enhanced learning for the future smart road. We reviewed 80 articles from sources such as Google Scholar, Elsevier, Springer, etc. This work reviewed machine learning algorithms, i.e., mechanisms within intelligent methods and reinforcement. This paper discussed resource allocation and management, cloud computing, and most of the issues that IoV applications that rely on fifth-generation networks face. This article examines a number of premature studies on the fifth-generation vehicle network architecture and discusses machine learning applications to enhance the allocation and management of IoV resources. The study also examined intelligence applications that have the potential to transform the way that the Internet operates by utilizing sixth-generation networks soon.

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