ROLE OF AI ML IN VEHICULAR COMMUNICATION

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***Abstract*—In this paper we are presenting a comprehensive survey of Artificial Intelligence and Machine Learning algorithms which are being used in VANET(Vehicular Ad-hoc Network). VANET is a wireless self organizing network that helps in making the communication among the vehicles or V2X efficient, secure, reliable and secure. Nowadays since AI and ML is growing and the integration of VANET with AI ML is done in need to make an adaptive, context aware systems which can handle dynamic traffic conditions efectively thus enhancing overall transportation efficieny and safety. Through a systemic survey, the paper identifies challenges, key trends and future directions of utilizing AI ML in VANET. This research serves as a valuable resource for all engineers, researchers and policymakers to see and evaluate the potential of AI ML in advancing vehicular communication.**

I. INTRODUCTION

The rapid urbanization leading to a projected 70 percent increase in population highlights the necessity for efficient vehicular communication systems [1]. Vehicular Ad-Hoc Networks (VANETs) serve as the cornerstone of Intelligent Transport Systems, offering real-time traffic analysis and safety features. VANET integrates diverse wireless access standards such as WiFi, Zigbee, and DSRC, relying on Roadside Units (RSUs) to facilitate Wireless Access in Vehicular Environments (WAVE). Despite its benefits in safety, infotainment, and traffic management, VANET confronts challenges like latency, bandwidth scarcity, and routing complexities. Leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques can mitigate these challenges, enhancing Quality of Service (QoS), Quality of Experience (QoE), and resource allocation within VANETs [2].

By employing AI-based Vehicle-to-Everything (V2X) systems, data from various sources like vehicles and infrastructure can be leveraged to improve data transfer safety and predict potential accidents [3], [4]. Automated AI solutions can enhance QoS and QoE metrics without user feedback, addressing issues like mobility, link stability, and path lifetime prediction [5]. ML algorithms, including Reinforcement Learning and Deep Learning, can optimize computational overhead and enable efficient data cleaning from sensors and multimedia devices. Additionally, integrating AI with Mobile Edge Computing or Fog Computing can provide Ultra-Reliable Low-Latency Communication (URLLC) and balance privacy with information sharing challenges [6], [7]. Moreover, AI-powered techniques like Anti-Malware and Intrusion Detection Systems can bolster VANET communication security [8]. This paper offers a comprehensive review of AI ML techniques' effectiveness in enhancing VANET efficiency across resource allocation, task offloading, QoS, QoE, energy efficiency, and Fog Radio Access [9].

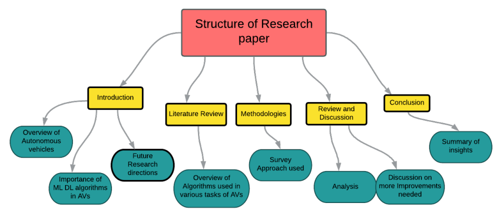

Fig. 1. Diagrammatic Organization of this paper

II. MOTIVATION

As wireless communication evolves, traditional Intelligent Transportation Systems (ITS) must adapt to meet heightened demands for security, speed, reliability, and efficiency, particularly in the context of Vehicular Ad Hoc Networks (VANETs). With a burgeoning vehicle population, issues like congestion and accidents are on the rise, with alarming statistics revealing a significant increase in road accidents and fatalities over the years [10]. The exponential growth in vehicle numbers, coupled with inadequate communication among vehicles, exacerbates these challenges. In 2022 alone, India recorded a staggering number of accidents, with a significant portion occurring on National Highways and

TABLE I
WORK SUMMARY OF ML TECHNIQUES IN FOG RADIO ACCESS

Ref	Learning Type	Approach	Application	Advantages	Future work/ Limitation
[28]	uSML	DOT-UCB	Contact Learning approach for optimization of resource sharing and task offloading in Fog based IoT network	Minimize long term delay	Encourage server sharing of computational resources
[29]	RL	MAB	Use of federated learning based in F-RANs for deployment of hierarchical AI deployment	Enhanced decision making, network optimisation and data processing.	Processing massive data accuracy(health monitoring(ITS)
[30]	DRL	DQN	Cloud edge cooperative offloading scheme in layered FRAN	Overcome capacity constraints and improve resource allocation	Achieve low latency content transmission and improved QoS and QoE
[31]	DL	CNN, DANN	Fault Detection in FRAN	Enhanced QoS in FRAN	Reduced missed detection rate.
[32]	FL	F-DL	Federated learning based cooperative hierarchical caching scheme(FLCH)	Preserve data privacy and enhancement of cache hit ratio.	Achieve a strict privacy guarantee

State Highways. Congested areas, commercial zones, and road features like sharp curves and potholes are prone to accidents. VANETs face security challenges such as privacy breaches and authentication issues, with attacks classified into various categories including accountability, confidentiality, availability, integrity, and authentication [11]. Malicious activities like eavesdropping and impersonation pose serious threats, leading to false information dissemination and potential hazards on the road. Addressing these challenges requires innovative solutions leveraging Artificial Intelligence (AI) and Machine Learning (ML) algorithms to enhance VANET security and communication systems [12]. This paper aims to explore and summarize the AL ML techniques proposed in recent research papers to address these critical issues in VANET networking and communication.

III. MACHINE LEARNING TECHNIQUES IN EMERGING WIRELESS NETWORK PARADIGM AND RESOURCE ALLOCATION

A. *Fog Radio Access Networks(F-RANS)*

The convergence of Fog Radio Access Networks (F-RANs) intertwines fog computing with radio access networks [**?**]. Within F-RANs, computation and storage are positioned in close proximity to users at the network periphery, thereby reducing service latency and easing traffic congestion. F-RANs serve as pivotal enablers for 6G wireless applications in industrial IoTs, D2D communications, and V2X communications, leveraging their inherent computational prowess and storage capacity to transcend the constraints of conventional C-RANs [13]. The proliferation of IoT devices precipitates a significant surge in data generation, imposing a formidable strain on traditional mobile networks [14]. Consequently, the integration of AI models, particularly machine learning algorithms embedded within the F-RAN domain, facilitates AI-driven F-RANs. This not only delivers real-time optimization for F-RAN operations but also enhances delay performance, conserves energy in content delivery, and mitigates the transmission overheads associated with network data collection [**?**].

Unsupervised Machine Learning (uSML) technique: uSML technique have found application in Fog Radio Access Networks (F-RANs) to tackle various optimization challenges concerning resource allocation, task offloading, and efficient communication. An illustrative example is a two-stage resource-sharing and task-offloading approach outlined in [**?**]. In this work, the authors devised a task-offloading algorithm leveraging computational intelligence and contract theory to enhance the delay performance of each User Equipment (UE). To mitigate the exploitation-exploration trade-off inherent in online learning for task offloading, the method harnesses the online learning capabilities of Multi-armed bandits (MAB). The authors introduced the DOT-VUCB method, empowering UEs to learn about the delay performance of each server based on factors such as occurrence time and proximity to fog servers. However, the proposed solution falls short in addressing cooperative communication among fog servers.

Deep Learning (DL): This technique is employed in Fog Radio Access Networks (F-RANs) for smart caching decisions, as discussed in [**?**], utilizing Bi-LSTM for popularity prediction. A proactive-reactive caching policy is formulated, incorporating content replacement, user location prediction, and popularity prediction. Trend classes are identified using k-Nearest Neighbor classifier and popularity prediction models, enhancing accuracy. However, computational complexity is overlooked. A deep transfer learning-based approach for fault detection in F-RANs is proposed, leveraging core-level information for spatial clustering-based fault detection. Unsupervised deep transfer learning with CNN and domain adversarial neural network improves convergence and detection accuracy. Nonetheless, privacy and adaptability concerns are unaddressed.

Reinforcement Learning(RL): In [**?**], researchers delve into the realm of caching applications within F-RANs by harnessing Reinforcement Learning (RL). They devise an AI-driven edge caching algorithm grounded in the multi-arm bandit (MAB) framework, tailored to the dynamic nature of fog nodes and cloud entities acting as agents. This endeavor addresses pertinent challenges including fluctuations in traffic demand

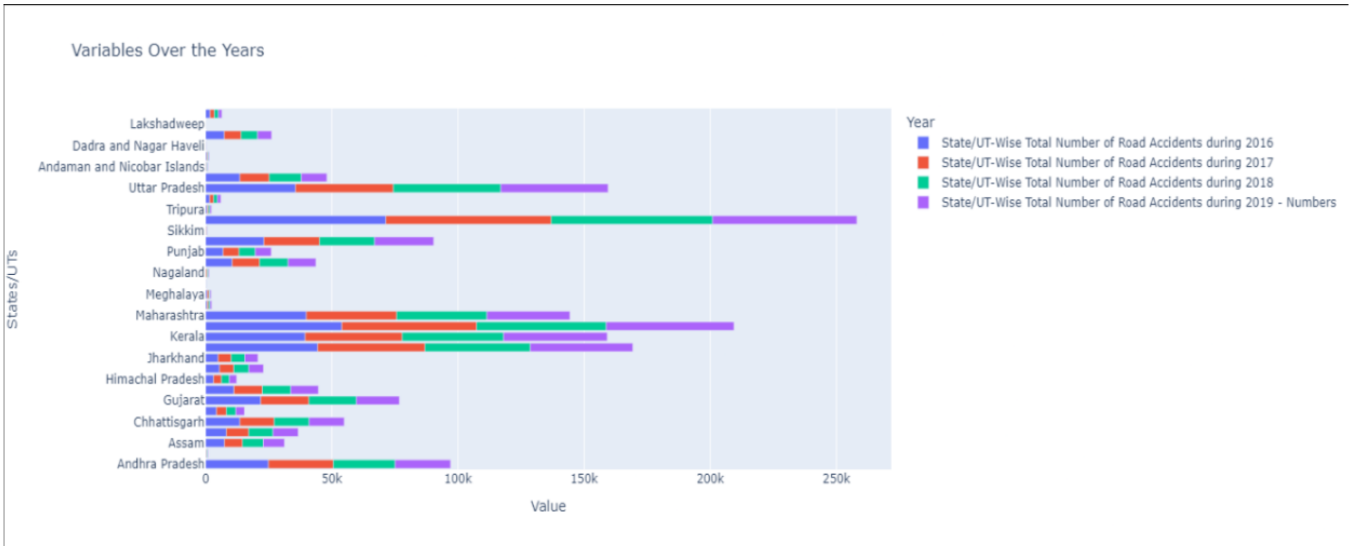

Fig. 2. Number of accidents from year 2016-2019 (INDIA)

and the inherent constraints of limited cache space. By considering spatial-temporal variability and the unpredictable distribution of content popularity, the proposed caching scheme outperforms benchmark approaches. It effectively enhances cache utilization at fog nodes and the cloud, resulting in a notable reduction in average end-to-end (E2E) delay.

B. *Task Offloading*

In the upcoming landscape of 6G wireless networks, a multitude of latency-sensitive and computationally intensive tasks will emerge. This is due to the integration of multiple radio access technologies, network slices, servers, and vehicular multimedia applications [**?**]. Real-time decision-making for task offloading becomes crucial for reducing latency and energy consumption. These decisions must occur within milliseconds to adapt to ever-changing channel conditions and system variables. However, as the user and task numbers grow, manually listing every potential decision becomes impractical. Recent literature investigates task offloading in Multi-access Edge Computing (MEC) system [**?**], [**?**], [**?**]. This includes a review of recent studies employing machine learning techniques (such as SML, uSML, DL, RL, DRL, and FL) to address task offloading scenarios.

Deep Reinforcement Learning (DRL): DRL has gained prominence recently for tackling optimization challenges in computation offloading due to its adaptability to complex and unpredictable environments. For instance, in [**?**], a DRL-based approach for computation offloading in Machine-Type Communication Devices (MTCDs) is introduced, optimizing energy consumption in both delay-tolerant and non-delay-tolerant scenarios. This method achieves efficient offloading without MTCDs needing awareness of MTC edges or cloud servers. However, challenges arise in implementing DRL algorithms in large-scale MEC networks, such as the exponential increase in state-action space and the risk of converging into suboptimal local solutions.

Federated Learning (FL): FL offers privacy protection for personal data and has been applied to task offloading in MEC systems [**?**]. FL maintains data privacy by transferring parameter updates instead of raw data. In [**?**], FL combined with DRL is proposed for task offloading in a wireless-powered communication-MEC system, enhancing convergence time and stability. However, task dynamics under system constraints are overlooked. [**?**]addresses computation offloading and service caching placement in UDNs using FL and two-timescale deep reinforcement learning, optimizing offloading time and network resources. Yet, user mobility's impact on spectrum usage is neglected. [**?**] explores computation offloading in space-assisted vehicular networks using an asynchronous federated DQN-based algorithm to reduce system delay and enhance throughput, though computation energy costs are not considered.

Deep Learning(DL): Various recent studies delve into machine learning-driven dynamic computation offloading in wireless networks [**?**]. For instance, [**?**] introduces a Distributed Deep learning-driven Task Offloading (DDTO) algorithm for decision-making in heterogeneous networks. It adjusts parameters adaptively, leveraging past offloading events in MEC and MCC environments to make near-optimal decisions. Despite its efficacy in reducing dimensionality costs, the approach overlooks privacy and adaptability concerns.

C. *Energy Efficiency*

Energy efficiency holds paramount importance in the design of 6G devices, especially with their utilization of

TABLE II
WORK SUMMARY OF ML TECHNIQUES IN TASK OFFLOADING

Ref	Learning Type	Approach	Application	Advantages	Future work/ Limitation
[38]	SML	SVM, NM	Resource allocation framework for EML based on stochastic Lyapunov optimization	Minimising energy consumption and optimising learning accuracy	Minimising trade off between energy delay and learning accuracy
[39]	USML	K means Clustering	EMF aware power allocation using convex optimization	Reduce EMF radiation exposure in cellular system	The proposed approach could be extended to multi-antenna systems
[40]	DL	DNN	Personalized optimized resource allocation in wireless networks	Saving resources and improved user satisfaction levels	Measuring and tracking user satisfaction in wireless networks is a key challenge
[41]	RL	Multi Q-learning	Resource allocation in ultra dense small cell networks	Maximise energy efficiency and minimise number of outrage users	Lower computational complexity
[42]	DRL	DQN	Integrated TDD configuration algorithm for dynamic allocation of radio resources	Improved network throughout less packet loss rate	Computation complexity is not addressed of proposed DRL approach

higher frequency bands. Intelligent machines like autonomous vehicles and drones necessitate D2D communication and base station connectivity, elevating concerns about sustainable wireless infrastructure due to increased energy consumption. In MEC-enabled IoT networks, fog nodes conduct low-latency computation offloading with limited resources. Integrating low-power communication systems with energy-efficient computing mechanisms can improve QoS, QoE, and sustainability for end-users in 6G wireless networks. Recent studies on ML-based energy-efficient communications are categorized into various machine learning types (SML, uSML, DL, RL, DRL, FL) [15].

Supervised Machine Learning(SML): SML has been utilized in recent studies to enhance energy efficiency across diverse next-generation wireless applications. In [15], supervised machine learning is employed for cache localization in D2D communications, reducing UE access delay and minimizing energy consumption. By leveraging decision trees and random forests, accurate cache placement locations are predicted. Authors introduce a trust factor to classify nodes, yielding higher accuracy with random forests compared to decision trees. Additionally, while energy consumption in D2D communication remains minimal, it escalates during content sharing between users and gateways.

Deep Reinforcement Learning(DRL): DRL techniques are applied in various scenarios to optimize energy efficiency in wireless networks. In [114], a DRL-based power optimization method is proposed for underlay D2D communication networks. Authors use parallel DQNs to enhance energy efficiency while ensuring QoS. However, the expansion of the action space with more users necessitates extensive exploration during training. In [**?**], joint optimization of resource allocation and mode selection in D2D-enabled heterogeneous networks is discussed using a DDPG algorithm. It achieves optimal policy based on continuous state and action space, improving convergence rate and energy efficiency. Yet, interference during D2D communications impacting QoS remains unaddressed.

Federated Learning(FL): Federated Learning with collaborative learning capabilities has gained traction recently, offering improved data privacy and energy efficiency [**?**], [**?**]. In [**?**] , a Federated DRL approach enables IoT devices to make real-time offloading decisions in edge computing-enabled space-air-ground integrated networks, optimizing energy consumption while considering privacy and communication failures. Similarly, [**?**] discusses joint optimization of resource allocation and task offloading in IoT networks using federated-double deep Q-network (F-DDQN) learning, showing superior performance in task execution delay and energy consumption. IT also presents a federated-deep reinforcement learning framework for joint optimization of user association and power control in UAV-assisted multi-access edge computing systems, outperforming benchmark schemes. Additionally, [**?**] considers resource allocation and user association in high-altitude balloon networks, reducing transmission energy and enhancing computation efficiency.

D. Latency Minimization

The forthcoming 6G communication systems aim for terabit-per-second data rates and minimal latency. Recent advancements in Massive Machine Type Communications (MTCs) and Ultra-Reliable Low Latency Communications (URLLCs) have transformed cellular communications. MTC facilitates diverse IoT connectivity like autonomous transportation and cognitive networks, each with unique Quality of Service (QoS) needs. However, conventional cloud servers may not meet the stringent latency requirements of these applications. Addressing these challenges requires integrating advanced ML techniques with 6G architectures and intelligent optimization methods. Recent studies on ML-based latency reduction in wireless networks are categorized into various machine learning types (SML, DL, DRL, FL) [15].

TABLE III
WORK SUMMARY OF ML TECHNIQUES IN ENERGY EFFICIENCY

Ref	Learning Type	Approach	Application	Advantages	Future work/ Limitation
[43]	FL	F-DRL	Trajectory design for RIS assisted Indoor Multi Robot communication system	Reduce convergence time by 86%, can adapt to the increasing number of robots and achieved higher energy efficiency	Transmit power analysis and saving computation overhead by reducing training dimension
[44]	RL	DBFL	Identification of distant devices of MEC architecture using clustering protocols	Increased classification performed by 7.4% and reduced energy consumption	Further studies could include more robust verification of DBFL
[45]	FL	F-SML, SVM	Task resources allocations in wireless High-Altitude Balloon Network	Minimised energy consumption and time consumption by 15.4%	Other models could be used to predict the optimal user association
[46]	FL	F-DRL	Resource allocation in UAV assisted MEC system	Reduced operation time by 23%	Improve system's throughout
[47]	FL	F-DRL	Edge computing of Remote things	Minimised energy consumption of task computation	Energy saving and computation efficiency

Deep Learning(DL): In [**?**], a Fast Uplink Grant (FUG) resource allocation method is proposed for massive IoT by prioritizing machine-type communication (MTC) devices using an SVM classifier and real-time MTD traffic prediction with LSTM. This approach minimizes access delay and boosts system throughput. Nonetheless, further investigation into appropriate exploration selection is warranted. Additionally it also tackles resource allocation in mobile edge networks through data sharing and distributed training, employing distributed Batch Gradient Descent (BGD) for CNN training. This method reduces training latency while improving speed and accuracy.

Deep Reinforcement Learning(DRL): In [16], a Deep Reinforcement Learning (DRL)-based approach is proposed for multi-channel access in high-mobility communication systems. Authors introduce deep deterministic policy gradients (P-DDPGs) to tackle challenges related to high-dimensional action space and slow convergence of DRL. The P-DDPG algorithm incorporates a learning-based DMCA framework comprising a Channel Prediction Module (CPM) and a P-DDPG module. This framework effectively reduces processing delay by leveraging system mobility features, enhancing convergence speed and reducing non-instant decision errors in channel access policy decisions. However, it does not address end-to-end latency concerns that could impact system reliability.

- *Federated Learning(FL)*: Recent studies have explored Federated Learning (FL) for optimizing wireless network performance, particularly in minimizing latency [**?**], [**?**]. In [**?**], federated learning is employed for node selection and cache replacement in collaborative edge caching within D2D-assisted HetNets, resulting in reduced average delay and improved hit rate and reward. However, security and privacy concerns in cache replacement remain unaddressed. [**?**] proposes a federated deep reinforcement learning model for enhancing QoS in UAV-based vehicular networks, aiming to minimize latency and enhance communication reliability, yet without considering fading effects.It investigates decentralized cooperative edge caching in IoT networks, utilizing a federated DRL-based framework to address duplicate traffic offloading and reduce average delay, enhancing cache hit rate and communication efficiency but overlooking user mobility's impact on communication efficiency.

E. QoE and QoS optimization

In the Internet of Vehicles (IoV), ensuring high Quality of Experience (QoE) poses a challenge due to dynamic communication topology. Flexible connections among IoV components are vital for enhancing user perception while minimizing power consumption. Cost-effective power and buffer-aware QoE optimization solutions are crucial, especially in sensitive applications like healthcare. Artificial Intelligence (AI) techniques revolutionize IoV networks by optimizing route selection and energy-efficient multimedia transmission. Machine Learning (ML) enables fault analysis and QoS evaluation, enhancing user satisfaction by addressing quality-degrading factors. ML frameworks analyze QoE services, leveraging data to optimize communication, energy, and resource management operations in IoV systems [9], [17].

Reinforcement Learning(RL): By employing RL algorithms it is studied that IoV networks can dynamically adjust buffer allocation and video-rate adaptation processes based on real-time feedback and environmental changes for example by using Q-learning approach. RL enables the system to learn and adapt its strategies over time, maximizing user satisfaction by prioritizing multimedia content delivery according to varying network conditions and user preferences. Through continuous interaction with the environment, RL algorithms enhance QoS by ensuring efficient resource utilization and minimizing latency, thereby improving QoE for users accessing multimedia streaming services in IoV networks [15].

TABLE IV
WORK SUMMARY OF ML TECHNIQUES IN QOS AND QOE OPTIMIZATION

Ref	Learning Type	Approach	Application	Advantages	Future work/ Limitation
[53]	RL	Q-learning	Energy optimization with 5G communication in VSNs	Maximise energy efficiently and data rate	Reduction of delays
[54]	SDN	BAT Algorithm	Data packet's prioritisation in IoT cloud storage	Enhanced Qos of traffic	Traffic delay in reduction in IoT
[55]	DL	Fuzzy based algorithm	QoS optimization for multimedia communication in IoV systems	Optimization of QoE at(31%-35%) and improved lifetime of portable devices at (25%-27%)	QoE optimization for multimedia communication in IoV
[56]	ML	CNN	Resource management and video admission control	Improved QoE and service level	Guarantee a minimum service quality level
[57]	RL	SMA, POMA	Plan aware schedule for EV charging	Improved QoE in vehicle power grid network	QoE enhancement in EV industry

Deep Learning(DL): Innovative fuzzy-enabled algorithms, coupled with AI-based frameworks, are revolutionizing Quality of Experience (QoE) optimization in multimedia communication within Internet of Vehicles (IoV) networks. These techniques, exemplified in studies by Sodhro [9], dynamically allocate buffers and optimize power usage, enhancing end-user satisfaction. By intelligently adapting to changing network conditions and user preferences, these methods ensure seamless multimedia streaming experiences. Sodhro's research highlights the significance of adaptive QoE optimization in IoV environments, laying the groundwork for future advancements. Through the integration of fuzzy logic and AI techniques, IoV systems can deliver unparalleled multimedia communication, elevating the user experience to new heights. Optimization of QoE is done till 31 percent-35 percent and improved lifetime of portable devices till 25 percent-27 percent.

Deep Reinforcement Learning(DRL): Bozkaya and Canberk [18] propose a novel approach to enhance the Quality of Experience (QoE) in Electric Vehicle (EV) industry networks, focusing on a many-to-one matching game framework. Their innovative Traveling plan-aware scheduling scheme for EV charging in driving pattern leverages Stable Matching Algorithm (SMA) and Pareto Optimal Matching Algorithm (POMA) to optimize charging schedules. By strategically matching EVs with charging stations, considering driving patterns and preferences, the scheme aims to minimize charging delays and ensure efficient energy distribution. This research addresses crucial challenges in the EV industry, paving the way for QoE improvements and enhanced utilization of vehicle power grid networks.

IV. CONCLUSION

This article provides a comprehensive review of recent studies of ML algorithms in Vehicular network covering techniques like supervised and unsupervised learning, Deep Learning, Reinforcement Learning, Deep Reinforcement Learning, and Federated Learning for resource management. It delves into ML algorithm implementations across Fog-Radio Access Networks, addressing challenges in resource allocation, QoS and QoE optimization and task offloading. The study also outlines ML-based approaches to enhance energy efficiency and reduce latency in 6G networks. It emphasizes the need for distributed ML architectures to tackle resource optimization challenges in 6G networks effectively. Moreover, the article advocates leveraging ML for intelligent resource management, facilitating self-healing and self-configuration in 6G networks for sustainable connectivity. It concludes by highlighting future research directions, envisioning novel ML techniques' integration into the design of 6G networks to automate processes, analyze big data, and realize intelligent edge, fog, and cloud nodes, aiming for seamless end-to-end connectivity.

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