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Survey paper

Towards artificial intelligence enabled 6G: State of the art, challenges, and opportunities

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ABSTRACT

6G is expected to support the unprecedented Internet of everything scenarios with extremely diverse and challenging requirements. To fulfill such diverse requirements efficiently, 6G is envisioned to be space-aerial-terrestrial-ocean integrated three-dimension networks with different types of slices enabled by new technologies and paradigms to make the system more intelligent and flexible. As 6G networks are increasingly complex, heterogeneous and dynamic, it is very challenging to achieve efficient resource utilization, seamless user experience, automatic management and orchestration. With the advancement of big data processing technology, computing power and the availability of rich data, it is natural to tackle complex 6G network issues by leveraging artificial intelligence (AI). In this paper, we make a comprehensive survey about AI-empowered networks evolving towards 6G. We first present the vision of AI-enabled 6G system, the driving forces of introducing AI into 6G and the state of the art in machine learning. Then applying machine learning techniques to major 6G network issues including advanced radio interface, intelligent traffic control, security protection, management and orchestration, and network optimization is extensively discussed. Moreover, the latest progress of major standardization initiatives and industry research programs on applying machine learning to mobile networks evolving towards 6G are reviewed. Finally, we identify important open issues to inspire further studies towards an intelligent, efficient and secure 6G system.

1. Introduction

With the rapid progress of 3GPP 5G phase 2 standardization and forthcoming commercial deployment of 5G system [1], many researchers [2],[3],[4],[5] from academia and industry have started envisioning what 6G will be. Giordani *et al.*[2] illustrated potential 6G use cases and potential enabling technologies. Zhao *et al.*[3] surveyed potential 6G technologies emphasizing artificial intelligence (AI), intelligent surfaces, and Terahertz communications. Huang *et al.*[4] presented a survey of potential technologies that are helpful to realizing sustainable 6G networks. Wikstrom *et al.*[5]described a set of potential challenges and possible technical components of the future 6G system. 6G is expected to support numerous novel Internet of Everything (IoE) applications such as extended reality (XR), holographic communications, smart environments, and brain-computer interactions. To fulfill the challenging and diverse demands in terms of performance, security and cost, emerging technologies such as ultra-massive Multiple-input multiple-output (MIMO) [6], holographic beamforming, large intelligent surfaces (LIS)[7], Terahertz (THz) communications [8], visible-light communications (VLC), and new network paradigm such as intelligent radio, AI native architecture, space-aerial-terrestrial-ocean integrated 3D networks are under extensive studies. The large dimension, super heterogeneous, extremely complex 6G networks should be flexible enough to provide customized services in dynamic environments. However, it is very challenging to manage the complex system efficiently by conventional manual centric approaches. Planning and optimizing the space-air-ground integrated networks with different types of radio access technologies are facing many unprecedented challenges [9]. The growing diversity of network services and the complexity of network systems make conventional network managing and optimizing approaches relying on mathematical models no longer adequate[10]. All the above-mentioned issues call for new approaches to achieve a 6G system that is flexible, adaptive, and intelligent to support diverse services efficiently without heavily relying on conventional management and optimization paradigms.

Recently, the typical AI technologies, especially machine learning

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(ML) and deep learning (DL) regained great attention from academy and industry due to successful applications in areas like computer vision, automatic speech recognition, and natural language processing [11]. Inspired by the great success, many researchers are attempting to introduce AI into mobile network systems. For example, ML/DL have been introduced to radio interface including upper layers such as cognitive radio [12], resource management [13], link adaptation [14] and physical layer such as modulation mode recognition [15],channel modeling [16], channel estimation [17], network security [18]. Bringing ML to the physical-layer can empower interference mitigation, resource management, and radio parameter estimation [19],[20][21]. made an in-depth investigation about the deep learning in wireless networks, and highlighted that traditional mathematical models based design techniques are very complementary to data-driven deep learning approaches. Besides, AI technologies have been applied to enhance the intelligence of the network, and reduce the complexity of network management and optimization [22]. Unlike conventional optimization technologies widely used in communication systems, ML-based solutions can automatically improve themselves through data-based training. The previous works have revealed that ML technologies are valuable to empower mobile networks from different perspectives such as network optimization [23], cognitive radio networks [24], sensor networks [25]. Moreover, [26] provides a comprehensive review of applying DL in intelligent traffic control. Chen *et al.*[27] reviewed ML-based traffic offloading solutions for wireless networks. Wu *et al.* [28] investigated the opportunity of applying AI and big data for green networks. Moreover, there have emerged several surveys on applying ML in mobile networks [29],[30],[31],[32][29]. made a comprehensive survey of solving wireless network issues by employing neural network techniques. However, it is limited to neural networks. Jiang *et al.*[30] briefly introduced ML and discussed some applications in 5G networks, but the discussions addressed only 5G radio access networks. Li *et al.* [31] discussed the relationship between AI and 5G, and highlighted the opportunities and challenges of employing AI to achieve intelligent 5G. But, they did not touch network security[32]. gave a high-level introduction of ML and exemplified some applications to communication networks, with an emphasis on the radio physical layer. Recently, Zhang *et al.*[33] made a comprehensive review of academic works on applying DL in different domains of mobile and wireless networks. However, they did not mention the industry studies from the practical network perspective. It is difficult for readers to clearly understand the gap between academic research and industry realization. Recently, the works [34],[35] shed light on the vision of the AI-enabled 6G system, but the two works do not have a holistic discussion of the typical network issues that can benefit from AI. Furthermore, most of the existing works do not provide concrete guidelines on how, when, and where to apply different AI techniques to solve typical mobile network issues. There is not a comprehensive review that can explain how to empower mobile networks with artificial intelligence to realize the visions of 6G. Therefore, this article makes a holistic survey on applying AI to mobile networks evolving towards 6G. The major goal is to present the state of the art and emerging research findings on combining AI with 6G mobile communications. By reviewing the latest literature, we discuss the key advantages and disadvantages of typical ML techniques and investigate ML-based methods to improve network performance by solving various complex network problems in dynamic environments. We wrap up the work by pinpointing important open issues to be well addressed for AI-enabled 6G.

The rest of this paper is organized as follows. Section II presents the vision of AI-enabled 6G. Section III discusses the driving forces of introducing ML into 6G. Section IV reviews the state of the art in AI. Major academic works on solving typical mobile network issues by ML are extensively discussed in section V. Then, section VI reviews the latest progress of the industry standardization and projects on developing networks towards 6G by leveraging ML. Subsequently, section VII points out potential future research opportunities towards AI native 6G. The survey is summarized in the final section.

2. The vision of AI-enabled 6G networks

2.1. 6G System framework envisioned

The 5G phased 1 standard defined by 3GPP R15 was frozen in June 2018, the 5G phase 2 specifications focused on massive Machine Type Communications (mMTC), and Ultra-Reliable Low Latency Communications (URLLC) are expected to be finished in 2020. Meanwhile, several global leading operators such as NTT DOCOMO and China Mobile, have started 5G trials since 2019 and plan to roll out commercial 5G systems in 2020 [36]. Historically, a new generation of mobile communication systems arises approximately every decade. Therefore, it is time to think about what 6G will be. Recently, many researchers from industry and academia have initiated the study of 6G [37],[38],[39],[40]. ITU has established a new focus group for network 2030 (FG NET-2030) [41]. The first 6G white paper [37] was published in September 2019. Subsequently, another 6G white paper [42] addressed the intelligence in the 6G edge. The roadmap towards 6G with emerging trends and requirements are discussed in [38]. Generally, a new generation system appears as a result of future social requirements and maturity of new technologies. To meet the increasingly stringent and diverse performance demands, and ubiquitous network coverage to everything in any place and at any time, Fig. 1 describes a multiple-domain mobile radio-to-optic oriented 6G networks. 6G system integrates a broad range of communication scenarios across multiple domains including space networks based on satellites, aerial networks based on unmanned aerial vehicles (UAV) [43], drones and high altitude platform (HAP), terrestrial networks serving indoor and outdoor users, and Internet of Things (IoT) devices, ocean networks based on ships and submarines. 6G radio access networks will be enabled by emerging technologies such as THz communications, visible-light communications (VLC), large intelligent surface (LIS), ultra-massive MIMO [35]. Besides conventional communication capability, 6G system will support multiple new capabilities including computing, content caching, and possible wireless energy transfer. The space-aerial-terrestrial-ocean integrated 6G networks should be realized by a unified system architecture to provide ubiquitous and flexible coverage, massive connectivity, and high-reliability [39]. To efficiently manage the complex 6G systems and orchestrate various resources across different domains in an automatic way, AI-enabled intelligent control and management functionalities are envisioned to be embedded at the center and edge of the network architecture to achieve a flexible, adaptive, and intelligent 6G system.

2.2. New services and requirements

2.2.1. Holographic applications

With rapid development in new display technologies, sensing and imaging devices, the virtual reality (VR), augmented reality (AR) and mixed reality (MR) technologies are evolving towards extended reality (XR). Emerging interaction services combining wearable displays and interaction mechanisms can create immersion into remote environments. The holographic services integrating multiple human senses such as taste, smell, touch, sight, and hearing are expected to provide a truly immersive experience. Holographics applications will demand a data rate in the order of terabits- per-second [44]. Due to the requirement of very low latencies and high data rate, the existing 5G system is incapable of providing such experiences combining multiple sensory inputs. The XR requires a combination of URLLC and enhanced mobile broadband (eMBB) besides incorporated perceptual factors that should be supported by 6G [45].

2.2.2. Intelligent manufacturing

Intelligent manufacturing aims to improve production efficiency and reduce human intervention in manufacturing processes by employing

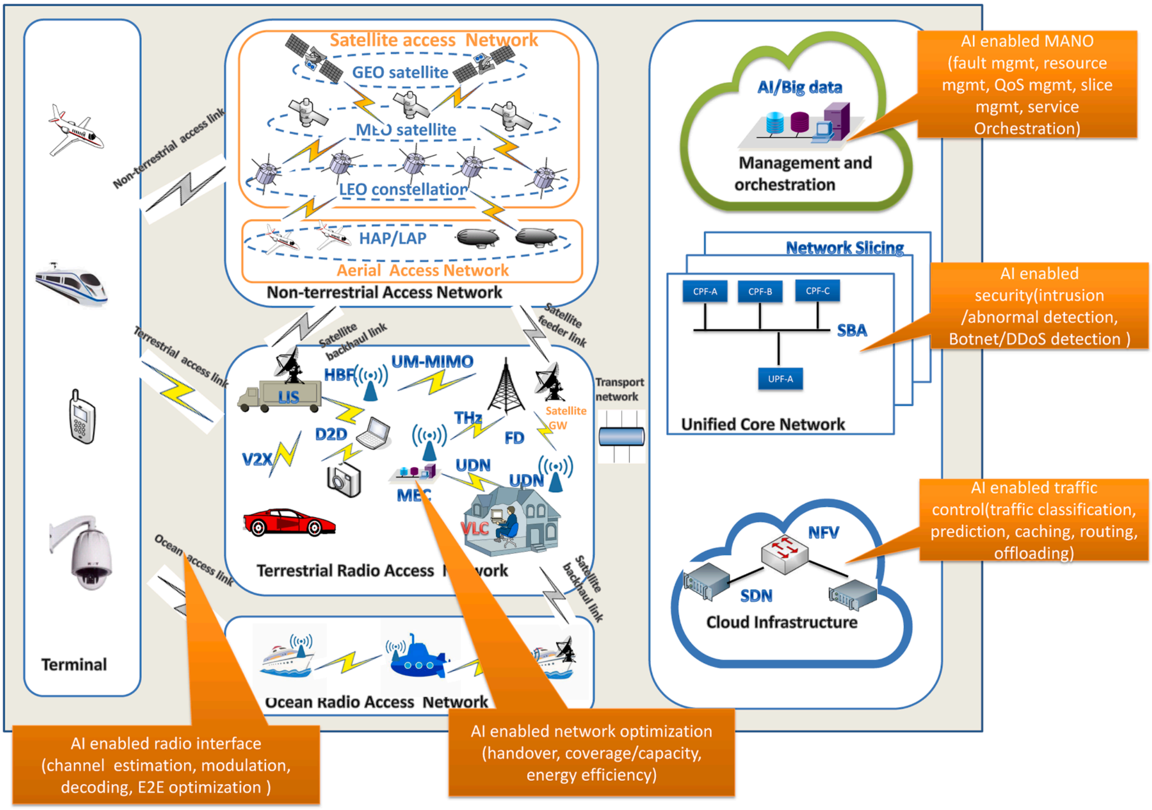

Fig. 1. An envisioned 6G framework.

automatic control systems and autonomous robotics,drone-delivery system, etc. It is based on the realtime and accurate control system, which requires extremely low latency on the order of 0.1-1ms and extremely high reliability on the order of 10^{-9} [46]. To assist accurate control, high definition maps from distributed sensors may be necessary. Moreover, some industrial control systems are characterized by strong determinism, which requires extremely low delay jitter on control message delivery. Overall, intelligent manufacturing scenarios pose stringent requirements across data rate, latency, jitter, and reliability.

2.2.3. *Smart environments*

The future smart and green environments are envisioned to improve the quality of people's life by providing multiple people-centered new services. The pervasive new applications can greatly contribute to smart environments such as intelligent transportation, smart grids, smart agriculture. These applications require pervasive sensing, data mining, intelligent control, and distributed actuation system, which pose stringent requirements. A large amount of data generated by the massive IoT devices can be effectively analyzed to generate instantaneous response only if high-quality wireless communication networks with strong computational capability exist. Meanwhile, the exponential expansion of IoT devices requires a significant enhancement on the connection numbers and coverage of 6G.

2.2.4. *Brain-computer interactions*

Brain-computer interaction (BCI) technologies can be used to establish a direct communication path between the brain and external devices. Based on wireless BCI technologies, people can interact with environments via embedded, or implanted devices, which makes it possible for people to interact with environments through minds and gestures. With the advent of BCI, new scenarios such as multi-brain controlled movies [47], new appliances used at home and medical system [48] may come into life in 6G time frame. Such empathic and haptic communications constitute an important type of use cases for 6G. In contrast to XR, the BCI based applications require physical perceptions and quality-of-physical-experience guarantees besides basic requirements like ultra-low latency, high data rate, and high reliability.

2.2.5. *3D Coverage extension*

With the expansion of the people's activity area, a larger three-dimension (3D) communication environment will be required. The 3D networks incorporating space, aerial, terrestrial, and ocean wireless access points and mobile edge devices are expected to provide economically efficient communication services to greatly changing requirements across time and space, such as sporadic events or disaster circumstances. Although the non-terrestrial network integration in 5G has been studied since R16, the standard and technical realization of the satellite networks and that of terrestrial networks are still independent instead of seamlessly integrated [49]. The system capability and efficiency of non-terrestrial network-integrated 5G can hardly meet the increasing requirement in a decade. The extreme 3D coverage poses new challenges on network planning and optimization, resource management, and routing due to the new dimension of altitude and associated degrees of freedom.

2.3. *New enabling technologies*

2.3.1. *Terahertz communication*

To fulfill the demanding data rate requirements from new services such as XR, the plenty of underutilized spectrum in mmWave and THz band can be exploited. Therefore, 6G networks need to explore various enabling technologies, such as THz communication, and Tiny cells to provide Tbps data rate service. The major challenge of THz communication lies in usable transceiver because it is too high for electronics-based devices and too low for the photonics-based device to generate THz signals [50]. Due to the challenge of the THz transceiver, the THz band is one of the least-exploited spectrum [8]. Recently, the graphene-based device is emerged as a promising transceiver to generate THz signals thanks to the extraordinary electro-optical features of graphene [51]. Given that THz signals suffer from the serious free-space path loss, which includes spreading loss and molecular absorption loss [50], the THz bands are more appropriate to short-distance wireless communications, such as wireless backhaul for tiny cells. To overcome the distance limitation, various potential technologies such as ultra-massive-MIMO (UM-MIMO) are under extensive studies [52]. THz communication will be mature gradually in the coming years and play an important role in the 6G area [53].

2.3.2. Visible light communication

VLC is another potential technology to provide the Tbps data rate by using the visible spectrum. The advantages of VLC include abundant unlicensed spectrum, very high-spectrum reuse, zero electromagnetic interference [54]. By using data-modulated light-emitting diodes (LEDs) as the transmitter and photodiodes as the receiver, VLC is a promising approach to provide extremely high bit-rates in Line-of-Sight (LoS) environment [55]. With the introduction of micro-LED based new light sources, the performance of VLC can be improved significantly to around 10Gbps with a single LED [46]. To achieve Tbps performance, the combination of micro-LED matrices and spatial multiplexing techniques needs to be studied furthermore.

2.3.3. Holographic radio paradigm

With the rapid development of advanced antenna technologies such as metasurface, reconfigurable intelligent surfaces (RISs) [56],a.k.a, large intelligent surfaces (LIS) [57]based on passive reflectarrays and controllable elements attract increasing attention in recent years. In contrast to conventional antenna arrays, LIS can break through the limit of half-wavelength with low cost and low energy consumption by spatially continuous radio signal transmitting/receiving aperture via an intelligent surface, which is constituted by a large number of passive reflecting elements with a controllable phase or amplitude. By manipulating the radio propagation environment in 6G wireless communications, RIS based intelligent radio can combat the unfavorable propagation conditions [56]. Facilitated by LIS, the holographic radio such as holographic MIMO [58], holographic beamforming (HBF) [59] are under rapid development recently. Holographic MIMO is capable of shaping electromagnetic waves to desired objectives via a low-cost transformative wireless planar structure comprising sub-wavelength metallic particles. HBF is a new beamforming technique using software defined antennas (SDAs) that employs dynamic beamforming architecture, which is based on passive electronically steered antennas. By holographic recording and reconstruction, HBF can generate desired beams flexibly to achieve higher spatial resolutions than conventional beamforming. Moreover, the holographic radio frequency (RF) based on LIS enables the closed-loop control of the electromagnetic environment through spectral holography and spatial wave synthesis to improve the spectrum efficiency and network capacity. Meanwhile, many open issues such as the optimum deployment of passive reflectors and metasurfaces, passive information transfer, and channel state information (CSI) acquisition, low-complexity design need to be well addressed to make holographic radio a reality.

2.3.4. Intelligent radio interface

The emerging software-defined metamaterial paradigm and configurable leaky wave antennas can greatly contribute to the intelligent 6G air interface. Reconfigurable antennas can bring a significant system gains by dynamically adapting beam patterns based on available CSI knowledge of each antenna state. The future antennas and metamaterial can be remotely controlled through ML algorithms in the form of software. Moreover, the software-defined cognitive radios can provide reliable wireless communications with efficient use of spectrum resources through intelligent operations based on knowledge learned from surrounding environments. ML can be naturally integrated into all operations of cognitive radios such as spectrum sensing, interference analysis, and dynamic spectrum resource management, power control. Besides, ML techniques open up the potential of jointly optimizing the end-to-end functionality chain of the physical layer. End-to-end learning aims to represent the entire communication system including the transmitter, wireless channel, and receiver with a single learning framework. The novel techniques make it possible to jointly optimize transmitter and receivers based on the end-to-end information recovery. Enhancing the intelligence of radio networks by ML to achieve self-management, self-protection, self-healing, and self-optimization is obvious for 6G networks [60].

2.3.5. AI Native network architecture

The cloudization, virtualization, softwarization and network slicing [61] are still important features of 6G architecture. However, intelligence will be the key feature to enable autonomous 6G networks. Enabled by native AI engines, 6G system can automatically orchestrate network structure and various resources including slices, computing, caching, energy, communication to fulfill changing demands. AI-based topology and resource management are important to efficiently adjust various resources utilization based on changing environments and dynamic user requirements. Given the growing computation and storage capability of the user devices, AI-based capabilities can be distributed to the network edge besides centralized intelligence. To overcome the limited computation, storage, power of the individual devices, leveraging the dispersed computing resources across network edges and end-devices through multiple access edge computing should be considered in 6G architecture. It is envisioned that intelligent services in 6G will span from data centers to edge network devices and user devices [35]. AI-based applications running on mobile devices or network edges can learn and predict user behavior, environmental circumstances, and act as context-aware assistants to centralized AI-based control systems. Meanwhile, to mitigate the concerns on data privacy and security of distributed training on edge devices, federated learning [62] can be employed to train data locally and learn the global model through sharing the learning models from distributed devices.

3. Driving forces of enabling 6G with AI

3.1. Channel modeling in complex scenarios

The accurate channel models representing real communication environments are important to the performance of the wireless communication system. Although the existing channel models can capture typical features of conventional wireless channels, they exhibit limitations in terms of imperfections and nonlinearities in some complex scenarios. For instance, the increasing number of antennas in massive MIMO communication has changed channel properties [63], which makes accurate channel modeling unknown. Moreover, for expected 6G scenarios such as molecular or underwater acoustic communications [64], it is very challenging to characterize the channels by rigid mathematical models. Therefore, it is time to explore new approaches to design a communication system without explicitly defined channel models. To this end, the data-driven paradigm does not need an accurate model to resolve the problem because the solution can be directly derived from the data generated by networks. By taking advantage of the data-driven model, DL can optimize the radio link performance by using large training dataset without any mathematically tractable channel model. Moreover, DL makes it possible to learn emergent channel models and adapt to new channel conditions by later training [65].

3.2. Effective and fast signal processing

As envisioned by [51], THz communication is valuable for 6G to fulfill the ultra-broadband real-time applications like XR and remote holographic communications for mobile users. The real-time large scale signal processing is necessary for future advanced 6G systems. Unfortunately, the conventional iterative reconstruction approaches, such as algorithms for data detection of MIMO leads to a computational bottleneck for real-time systems. In contrast, the neural networks can be implemented with highly parallelized on concurrent architectures and low-precision data types. It has been demonstrated that DL algorithms in this form could be executed faster and at lower energy cost than conventional programmed counterparts [66]. Therefore, parallel signal processing approaches are valuable to improve the efficiency and accuracy of future radio interfaces. The graphics processing unit (GPU) based parallel computing makes it possible for the DL to draw accurate inferences within milliseconds.

3.3. Limitation of existing radio system

To solve the complex radio communication issues, the divide-and-conquer approach is widely employed. Accordingly, the existing communication systems are designed with a series of defined blocks, such as channel coding and decoding, modulation and demodulation, etc. The radio communication problems are usually solved by optimizing each function block independently. Although many researchers have attempted to optimize each specific block and achieved certain gains in practice, the optimal performance of the entire system can not be guaranteed [20]. The reason behind this is that the essential problem of communication depends on the successful message recovery by the receiver after the transmitter sends the message through the wireless channel [67]. The process does not necessarily require an artificial block structure. Therefore, it is time to optimize the system performance from the end-to-end perspective instead of optimizing each block independently. In this regard, the reinforcement learning approach like autoencoder makes it possible to holistically optimize 6G radio interface from an end-to-end perspective.

3.4. Diverse QoS/QoE requirements

6G is envisioned to support various new IoE applications such as XR, intelligent manufacturing, smart environments, etc. It is challenging to understand, evaluate, and ensure satisfying QoS/QoE of emerging applications. Most existing QoE models are limited to conventional mobile broadband services such as Voice over LTE (VoLTE), streaming. To establish an accurate Quality of Service (QoS)/ Quality of Experience (QoE) model, user demands, and characteristics of new applications should be learned deeply. ML techniques have been found useful in finding the correlations between application-level QoE metrics and network-level QoS indicators and understanding the impact of QoS on the QoE. Furthermore, 6G is expected to provide various services with space-aerial-terrestrial-ocean integrated 3D coverage, it is very challenging to maintain a consistent and satisfying user experience in such complicated and dynamic network environments. Besides existing reactive QoS/QoE, proactive QoS/QoE management mechanisms based user behaviors awareness, network status awareness, and future demand prediction is of great importance. ML has been demonstrated as an effective approach to fulfill extreme and diverse requirements from various new applications by predicting user behaviors and traffic demands.

3.5. Complex and flexible networks

6G is expected to be a space-aerial-terrestrial-ocean integrated network with different access networks presenting distinct characteristics. Moreover, as a result of ultra-dense networks, and flexible control-data plane separations, there is a significant increase in the number of network nodes in various formats such as macro-station,micro-station, Femto station, central unit (CU), distributed unit(DU), active antenna unit (AAU), to be managed by network operators. It is increasingly challenging to configure and manage such complex networks with conventional approaches, which heavily rely on human efforts. One possible solution to enhance the intelligence of the network management system is leveraging ML/DL to achieve the vision of a self-sustaining network [45], which is expected to not only adapt network functions but also sustain network resource usage to autonomously maintain long term performance. Furthermore, network slicing makes it possible to provide various customized services over common physical network infrastructures. The running network slice instances need to be scaled flexibly to fulfill changing customer demands. With an increasingly large number of network slice instances across space, aerial, and terrestrial network domains, it is more challenging for operators to manage and orchestrate sliced 6G network resources efficiently. To this end, ML is a promising approach to enabled intelligent network management and slice orchestration.

3.6. Efficient resource utilization

The existing smartphone-centric communication ecosystem is evolving into a 6G IoE ecosystem that integrates various devices such as drones, connected vehicles, sensors, etc. The transformation will lead to exponential growth in data traffic. To provide high data rates, 6G networks will utilize various spectrum resources, such as low radio frequency, mmWave, Terahertz, and visible light spectrum. It is very challenging to efficiently utilize various spectrum resources for diverse applications/users in dynamic network environments. Moreover, the available radio resource is quite limited although high-frequency spectrum such as mmWave, THz is exploited. Therefore, the limited network resource must be utilized intelligently and flexibly to fulfill diverse and changing user demands. Besides, Tiny cells are expected to be introduced in 6G [60] to improve network capacity by increasing spectrum reusing. However, it requires efficient management of increasing inter-cell interference. To this end, 6G should accommodate a paradigm shift from conventional network resource scheduling to AI-based intelligent resource management. With the help of AI, various spectrum resources can be efficiently used to transmit diverse traffics with different requirements. Deep reinforcement learning makes it possible to establish a closed-loop automated optimization framework to utilize various network resources efficiently.

3.7. Lower energy consumption

Increasing the energy efficiency of the mobile network is helpful to reduce operational expenditure and carbon emissions for sustainable development. The data explosion combined with the increasingly large number of tiny devices makes the energy consumption of 6G particularly challenging. Furthermore, the complexity of transceiver processing and increasing end-user applications may lead to more energy consumption [37]. Energy efficiency can be improved by many techniques such as dynamic cell operation, traffic offloading, etc [68]. Meanwhile, energy consumption can be reduced by exploiting green energy resources. Energy harvesting methods, simultaneous wireless information, and power transfer (SWIPT) [69] have been proposed to exploit green energy from natural resources such as the sun and wind. To overcome the shortage of stochastic and intermittent availability of natural resources, user mobility and traffic characteristics need to be considered to take proactive energy management measures. The ML algorithms can be leveraged to learn the wireless environment and derive the appropriate configuration to achieve expected objectives. To optimize energy consumption while ensuring user experience, it is important to learn dynamic user traffic patterns and mobility patterns, weather situations, and make predictions about future traffic demand and green energy availability. However, conventional optimization methods and heuristic algorithms are not sufficient to perform these complex tasks [10]. Fortunately, ML algorithms can be employed to learn the optimized policy for the energy-saving objective of the complex and dynamic radio network environments [70].

3.8. Increasing security and privacy threats

With the popularity and advancement of smartphone devices, malware and virus-infected mobile applications lead to numerous threats to network security and user privacy. Besides mobile broadband service, 6G is expected to support various IoE applications. Due to constrained processing capability and energy provision, it is more challenging to enforce sufficient security protection for simple IoT devices. The botnet is becoming a serious threat to mobile networks, especially in the case of massive IoT scenarios, where large numbers of cheap devices under high risk of being hijacked. Effectively detecting botnet is challenging and critical to 6G network security. Moreover, public awareness of privacy protection has increased significantly, which leads to more concerns about user privacy leaking. With the upcoming smart environments, such as health care, autonomous vehicles, there are higher demands for privacy protection. Furthermore, ML has been misused for cyberattacks, such as guessing user passwords or compromising user privacy information[71]. Meanwhile, ML has been widely used in cybersecurity applications, such as intrusion detection, anomaly detection, botnet detection, security situation awareness, etc. Assisted by ML, it is possible to establish a closed-loop security protection framework, where abnormal traffic collection, data mining, risk detection/prediction, policy control/decision making, security resource orchestration, security policy enforcement can be performed automatically for intelligent, proactive, flexible 6G security protection.

4. The state of the art in AI

AI is a multi-disciplinary science that develops theories, techniques, methods to simulate and extend human intelligence [72]. AI attempts to understand the essence of intelligence and simulate the information processing of the human brain by machines. As a branch of AI, ML is related to computational statistics and predictions by exploiting the experience and knowledge gained from data [73]. DL is essentially a branch of ML, which enables a model to make classifications, predictions, or decisions based on large datasets, without being explicitly programmed. Fig. 2 illustrates the relations among AI, ML,DL.

4.1. Machine learning

ML is about learning from data and making decisions or predictions [74]. It is essentially based on the assumption that machines can be endowed with intelligence that enables them to learn from previous computations and adapt to the environment. The history of ML dates back to 1943 when the mathematical model of the neural network (NN)

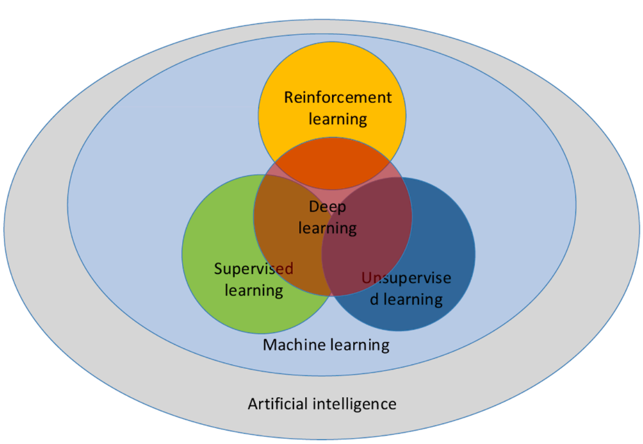

Fig. 2. The relationship of AI, ML and DL.

for computers was first proposed by McCulloch[75]. The typical ML framework includes a training process and a testing process. The former enables the ML framework to discover the relationships between input data and output data. The existing ML models can be categorized into classification models, regression models, and structured learning models. The classification models are used to solve binary classification or multiple classification problems. The regression model can be used to perform prediction. The structure learning model is widely used in many fields such as natural language processing, etc. According to the training method, the ML can be categorized into supervised learning, unsupervised learning, and reinforcement learning (RL) [76]. Fig. 3 shows the classification of major ML techniques.

4.1.1. Supervised learning

Supervised learning requires a supervisor to label the input data and output data. In the training phase, the learning algorithm is fed with a set of labeled training dataset containing input and known output to train a model representing the relations between input and output. In the test phase, a new set of test data is fed into the learned model to get the expected output. Supervised learning is usually used in scenarios with enough labeled data. The method has been widely used in many fields, such as object recognition, speech recognition, and spam detection. Typical algorithms in this category include Naive Bayes, K-nearest neighbor (KNN) [77], random forest [78],neural networks (NN), support vector machine (SVM), decision trees (DT).

- **K-Nearest Neighbor**: KNN is a classification algorithm based on measuring the distance between different feature values. The classification of a data sample is determined based on the class of K nearest neighbors. If most of the K nearest neighbors in the feature space belong to a certain category, then the sample is categorized into the same category. The algorithm is easy to realize, insensitive to outliers, and suitable for multiclass classifications. But it is very time-consuming when used for large datasets.
- **Decision tree**: Each node of the decision tree represents a feature of a data, each branch represents the conjunction of features that lead to classification, and each leaf node represents a specific class. The decision tree is built to maximize the information gain of each variable split, which results in a natural variable ranking. ID3 and C4.5 are well-known algorithms to build decision trees automatically. The classification of the unlabeled sample can be achieved by comparing its feature value with nodes of the decision tree, which is trained by the labeled dataset. The major advantages include high classification accuracy, simple implementation, and intuitive expression. However, it suffers from data including categorical variables with a different number of levels because information gains will be biased to features with more levels.
- **Random forest**: A random forest usually consists of multiple decision trees. To mitigate the over-fitting issues of the decision tree, the method randomly selects a subset of features to construct each decision tree. A new dataset is classified by each decision tree, then the data sample is categorized into a class that is agreed upon by most trees.
- **Neural network**: The neural network can be used to learn experiential knowledge from historical data by a large number of processing units, which operate in parallel. Activation functions such as sigmoid and the hyperbolic tangent functions are usually applied to these units to realize nonlinear computations. A neural network usually has one input layer, one output layer, and one or more hidden layers. By tuning the number of hidden layers and the number of units in each layer, different models can be trained to solve classification or regression issues. The neural networks model can be trained by supervised learning or unsupervised learning.
- **Support vector machine**: The objective of SVM is to maximize the margin between different classes by finding a best-separating hyperplane in the feature space. To distribute the input vectors into

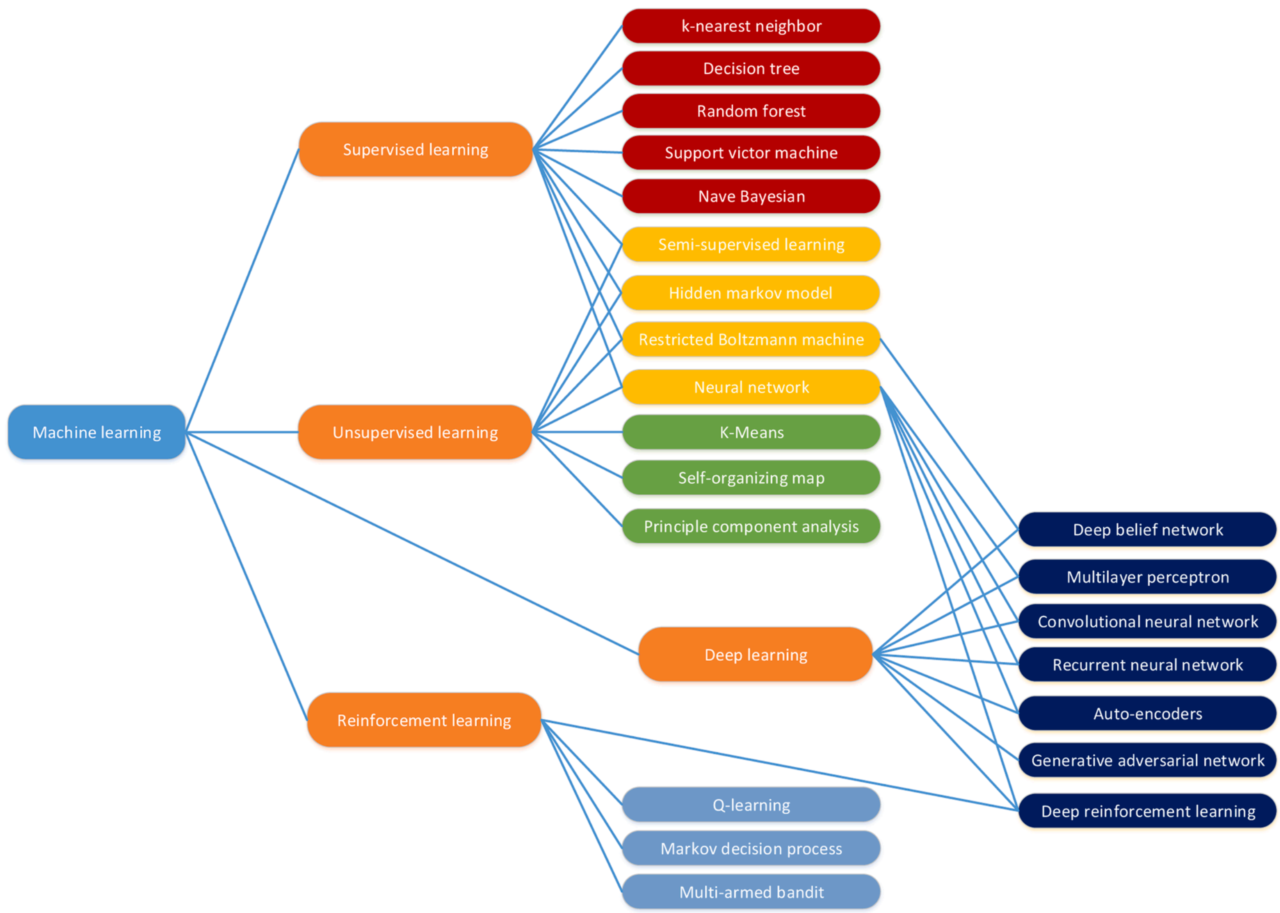

Fig. 3. A summary of typical ML methods.

feature space, different kernal functions such as linear, polynomial, and radial can be used. Kernal function selection is very important because it depends on the training dataset and has a significant effect on classification accuracy. The method has been widely used for classification and pattern recognition. In general, the method is stable and can achieve a low false alarm rate for binary classification tasks.

- **Naive Bayes**: it is a simple probabilistic classify approach based on Bayes theorem. The classifiers can effectively handle a large number of continuous or categorical features that are independent because it can transform a high-dimensional density estimation task to a one-dimensional kernel density estimation task based on the assumption that features are independent. The naive Bayes classifier can be used as an online algorithm since it can be trained in linear time [79].

4.1.2. Unsupervised learning

The unsupervised learning algorithms are given a set of unlabeled input to correctly infer the output. The techniques are usually used for clustering and aggregation. Typical unsupervised algorithms include K-means [80], self-organizing maps (SOM) [81], hidden Markov model (HMM) [82], Restricted Boltzmann machine(RBM).

- **K-means**: It is widely used to classify a set of unlabeled data into different clusters. K represents the number of desired clusters. The objective function of k-means represents the distance between data and associated centroids. K-means tend to assign each data to a cluster with the centroid that is nearest to the data. The process of updating centroids based on an assigned data point will be repeated until no point or centroid changes. The selection of K has a great impact on the performance of the algorithm.
- **Self-organizing map**: SOM is often used to realize dimensionality reduction and data clustering. SOM contains one input layer and one map layer. Each layer includes many neurons and each neuron has a weight vector. During the training process, SOM can build and reorganize the map. Unlike conventional NNs that apply error-correction learning, SOMs use an unsupervised competitive learning approach [83]. After training, a new input vector is classified into a cluster based on the winning neuron on the map. The techniques have been successfully used in various pattern recognition tasks.
- **Hidden Markov model**: The approach can be used to modeling a system by a Markov process with unknown parameters. The main challenge is to determine the hidden parameters from known parameters. Markov models [84] are widely used in randomly dynamic scenarios with memoryless property, which means the conditional probability distribution of future states only depends on the current state. The parameters of HMM can be trained in a supervised or unsupervised way. The HMM can be used to represent non-stationary sequences, which allows the system to change over time with different output probability distributions of each state.
- **Restricted Boltzmann machine**: An RBM represents a stochastic NN that consists of two layers: the input layer and the hidden layer. Compared with the basic Boltzmann machine, the RBM does not permit the connections between any two units in the same layer [85]. The learning process of RBM is efficient thanks to the restriction on connections within any layer. Once an RBM is trained, the activities of the hidden units can be used to train a higher layer RBM. The method makes it possible to train stacked RBM with many hidden layers efficiently. After pre-training, the RBM can be unfolded to construct a deep network that can be fine-tuned by the

back-propagation algorithm. As the method can be trained in supervised or unsupervised ways, RBM is useful in a variety of domains such as feature learning, classification, and dimensionality reduction.

4.1.3. Semi-supervised learning

Semi-supervised learning is a combination of supervised learning and unsupervised learning. In many real-world scenarios, generation a large amount of labeled data is expensive and time-consuming, whereas it is relatively cheap and convenient to collect sufficient unlabeled data. Therefore, semi-supervised learning is developed to make full use of unlabeled data to improve the performance of the trained model [86]. As a typical example of the semi-supervised learning algorithm, the Pseudo labeling [87] is simple and efficient. The limited labeled data is used to train a model. Then, the trained model is used to generate the pseudo labels for the unlabeled data. Finally, the labeled data and the pseudo-labeled data are used to retrain the model. To make full use of unlabeled data, semi-supervised learning algorithms usually require certain assumptions on the dataset, such as manifold assumption, low-density assumption, cluster assumption, and smoothness assumption [88]. For instance, expectation-maximization is based on cluster assumption, while transductive SVM requires the low-density separation assumption.

4.1.4. Reinforcement learning

The main idea of reinforcement learning (RL) is to imitate the learning process of the brain by trial and error [89]. Instead of learning the structure of the training dataset, RL tries to explore the best actions during a dynamic process. The capability to understand the environment through actions and feedback makes it suitable for solving decision-making issues. The RL can be categorized into two types: model-based and model-free. The model-based RL framework includes an agent, a state-space, and an action space. Through interacting with the environment, the agent tries to represent the model of the environment and learn the best action to maximize its long-term reward, which is a cumulative discounted reward and relates to both the current rewards and future rewards. At each step, the agent monitors a state and takes an action from action space, then it receives an immediate reward indicating the effect of the action, then the system moves to another state. In model-free based approaches, the agent tries to learn a policy. During the state transition process, the agent learns the best policy which is a map from state to the action space to maximize the long-term reward. To determine the long-term reward of action in a state space, the value function is applied. The most widely used value function is Q-function, which is used by the Q-learning method to learn a table to maintain state-action pairs and associate long-term rewards. Model-free based RL is more suitable for mobile networks due to the difficulty of building an accurate model of dynamic networks [90]. Compared to other learning techniques, the major advantage of reinforcement learning is that it does not depend on an exact mathematical model of the environment. Besides, the approach addresses the long-term rewards including both the immediate rewards and those in the future, which enables long term optimization result. How to design the system state, action, reward in different scenarios to converge the optimal performance is the main challenge of applying RL to the wireless communication system. In recent years, the RL has been widely employed to solve the decision-making issues of wireless communications, such as user scheduling [91], spectrum sharing [92], radio access technology handover [93]. However, the technique faces some challenges in handling problems with a large state space or action space because it is very difficult to model every state-action pair directly. Consequently, RL is rarely used in practice.

4.2. Deep learning

In contrast to conventional ML algorithms that rely on pre-defined features, DL [94],[95]can extract essential features from raw data through multiple layers of nonlinear processing units to make predictions or take actions based on the target objective. The major advantages of DL are automatic feature extraction. The most well-known DL models are neural networks with a sufficient number of hidden layers. Although the multi-layer neural network was proposed several decades ago, it only draws unprecedented interest recently thanks to the breakthrough of back-propagation based training [96] and the success of GPU. The major objective of deep neural network (DNN) is to approximate any complex functions by a composition of simple operations on neurons. DL can automatically extract essential features from input data with complex structure. It does not need a human-designed learning process, which significantly reduces the effort on feature handcrafting. DL can learn valuable patterns from unlabeled data in an unsupervised manner. The main challenge of employing DL in the mobile communication system lies in the design of optimal deep neural networks for different scenarios so that the model can be efficiently trained in the off-line stage and achieve good performance in the online testing stage. Typical DL models include multilayer perceptron (MLP), deep belief network (DBN), auto-encoders, convolutional neural network (CNN), recurrent neural network (RNN), generative adversarial network (GAN).

4.2.1. Multilayer perceptron

Multilayer perceptron [97] is a primary artificial neural network (ANN) model, which consists of at least three layers: an input layer, more than one hidden layer, and an output layer. It requires that units in neighboured layers are densely connected, therefore a large number of weight parameters need to be trained. The MLP model can be used for supervised learning, unsupervised learning, and RL. Although the model was widely used in the past, it is not frequently used due to high complexity, low convergence speed, and modest performance. MLP can be used as a baseline for advanced architectures. For example, advanced adaptive learning neural Network (AdaNet) makes it possible for MLPs to dynamically adapt their structures to the training dataset [98], which can be explored for optimizing continuously changing mobile networks.

4.2.2. Deep belief network

The deep belief network (DBN) is a type of generative NNs that represents the first successful DL model. A DBN can be built by stacking several restricted Boltzmann machines (RBM) [99]. The training of a DBN can be performed layer by layer, where each layer is treated as an RBM trained on top of the previously trained layer [100]. The layer-wise training makes the DBN as an efficient DL model. DBN can use unsupervised learning to extract multiple layers of features that are used in the feed-forward network. The supervised pre-training makes the DBN less prone to overfitting issues. DBNs are suitable for hierarchical features discovery and achieves good performance in many applications like forecasting.

4.2.3. Auto-encoder

The auto-encoder (AE) refers to a special kind of NN aiming to learn efficient coding by encoding the input dataset. The encoded data represents a compressed format of the input dataset. Auto-encoders are designed as an unsupervised learning approach to learn the compact representation of input data. Therefore, the auto-encoder can be used to perform data compression or dimensionality reduction. The typical auto-encoder model includes an input layer, one or more hidden layers, and an output layer. The hidden layers are used to encode the input dataset while the output layer attempts to reconstruct the input layer from the coded dataset. In conventional AE, the hidden layer is much smaller than the input and output layer. The AE can be used to extract patterns from unlabeled mobile data, and the patterns are subsequently used for various supervised learning tasks [33]. Based on the basic auto-encoder structure, the advanced denoising autoencoder (DAE) [101] has been developed to reconstruct the input from a noisy version of input data. By using multiple layers of autoencoders, stacked autoencoder (SAE)[102] can be trained in series to gradually compress the input information.

4.2.4. Convolutional neural network

Convolutional neural network (CNN) [103] is another emerging deep neural network (DNN) architecture that is evolved from the fully connected feedforward network to avoid rapid growth in parameters. The basic concept of CNN is to introduce convolutional and pooling layers before feeding input to a fully connected network. Each neuron in the convolutional layer only connects to partial neurons in the previous adjacent layer. These neurons are organized in matrix form to represent feature maps, and neurons in the same map share the same weights. In the pooling layer, neurons in the feature maps are grouped to compute for the mean weight value or maximum weight value. In this way, the parameters to be trained are significantly decreased before using fully connected networks. The major strength of CNN is learning the feature hierarchies from a large amount of unlabeled data. CNN improves the conventional MLP by leveraging three techniques including parameter sharing, equivariant representation, and sparse interactions. Thanks to these unique features, CNN shows very good performance in imaging processing applications.

4.2.5. Recurrent neural network

The recurrent neural network (RNN) aims to provide neural networks with memory. Unlike conventional feedforward networks, the output of RNN depends on both current computations and previous computations. In principle, RNN can process any length of sequence data. The neutrons in hidden layers are connected so that the hidden layers can use their former outputs as current inputs to achieve memory. The back-propagation method is usually employed to train the network model of an RNN. However, the gradient vanishing or exploding problems make it very hard to train normal RNN [104]. To cope with these issues, the long short term memory networks (LSTM) [105],[106] and gated recurrent unit (GRU) methods are developed in recent years. The RNNs are often used to address sequential or time-series problems such as natural language processing.

4.2.6. Generative adversarial network

The generative adversarial network (GAN) [107] refers to a framework that trains the generative models by using an adversarial process. The framework consists of two models: the generative model is used to approximate the target data distribution from training data, the discriminative model estimates the probability of the data comes from real training data rather than the output of the generative model. The generator and the discriminator are trained iteratively. The objective of the training process is to maximize the probability of discriminator making the wrong decision. Therefore, the generator will produce data close to real data distribution. Training conventional GAN is very challenging because it is very sensitive to model structure, learning rate, and hyperparameter settings.

4.2.7. Deep reinforcement learning

By leveraging the powerful data representation capability of the deep neural network, the deep reinforcement learning (DRL) [108] emerges and shows promising capabilities to solve complicated problems in the dynamic radio environments with a large state-action space [109]. DRL refers to methods that approximate value functions or policy functions by DNN, which makes it possible to handle decision-making problems with high dimensional state and large action space. DRL relies on DNN for approximating the best policy. Typical DRL methods includes Deep Q-Networks [110], deep policy gradient [111]. These methods demonstrate good performance in autonomous driving, robotics, and gaming. As one of the most successful examples of DRL, AlphaGo depends on a DNN trained by using supervised learning, RL, and conventional heuristic algorithms. Many mobile network issues can be formulated as the Markov decision process, where DRL can be employed to make the optimal decisions in long term, such as routing, tracking control of MIMO, adaptive cell switch on/off for energy saving, etc.

5. AI Empowered networks towards 6G

Currently, ML and DL have been employed to empower mobile networks from almost every perspective. Fig. 4 shows a summarization of AI-enabled mobile network functionalities including radio interface, intelligent traffic control, network management and orchestration, network optimization, and network security.

5.1. Advanced radio interface

5.1.1. Channel estimation and detection

As new 6G scenarios such as molecular communications and new technologies such as UM-MIMO, mmWave, THz communication emerged, future radio communication channels are becoming more complex. Therefore, it is more challenging to efficiently estimate the channel status. To achieve high-resolution channel estimation, Ye *et al.* [112] developed a DNN based channel estimation framework for the orthogonal frequency-division multiplexing (OFDM)system. After training the model under different channel conditions, the output generated by the DNN can recover the input symbols without requiring explicit channel detection. Simulation results show the method outperforms conventional methods. Besides, CNN has been considered for MIMO channel estimation. Neumann *et al.* [113] designed a lightweight, approximated maximum likelihood estimator by exploiting the structure of the MIMO channel model, it is demonstrated that the CNN based methods outperform conventional estimators in terms of computational complexity. Furthermore, Oriented to the direction of arrivals (DOA) estimation and channel estimation issues of massive MIMO, [114] proposed an approach based on the DNN framework. After offline training of the DNN, the approach outperforms other schemes in terms of Bit Error Rate (BER). Besides, [115] proposed an interesting idea of employing DL for channel estimation of massive MIMO. To achieve good channel estimation performance with lower CSI overhead, a DNN framework consists of an encoder and a decoder is proposed. The encoder transforms the vector in codewords by compressive sensing, then the decoder recovers the CSI based on CNN and RefineNet. It is claimed that the method achieves superior channel estimation performance with low complexity.

Moreover, Since conventional iterative detection methods lead to a negative impact on real-time implementation, many researchers resort to DL methods for channel detection by unfolding specific iterative detection algorithms. By leveraging the flexible layer structures, DL based detection approach can make an appropriate tradeoff between detection accuracy and computational complexity. In [116], Samuel *et al.* proposed a DL-based detector called DetNet to reconstruct transmitted signals by using received signal and channel matrix as inputs to layered structure, and optimize the maximum likelihood by unfolding the projected gradient descent algorithm. Simulation results indicate that DetNet achieves similar accuracy as conventional algorithms with much less time. Moreover, to deal with the new scenarios without mathematically tractable channel models, Farsad *et al.* [64] investigated the performance of several DL methods including fully connected CNN, DNN, and RNN for channel detection in molecular communication. The test results demonstrate that these DL-based detectors outperform the conventional detector. Especially, the LSTM-based detector shows an outstanding performance in the molecular communication scenarios even with intersymbol interference.

5.1.2. Modulation recognition

Modulation recognition aims to identify modulation types of the received signals. Conventional approaches include several procedures such as preprocessing, feature extraction, and classification. By leveraging the nonlinear processing capability,self-adaption, and

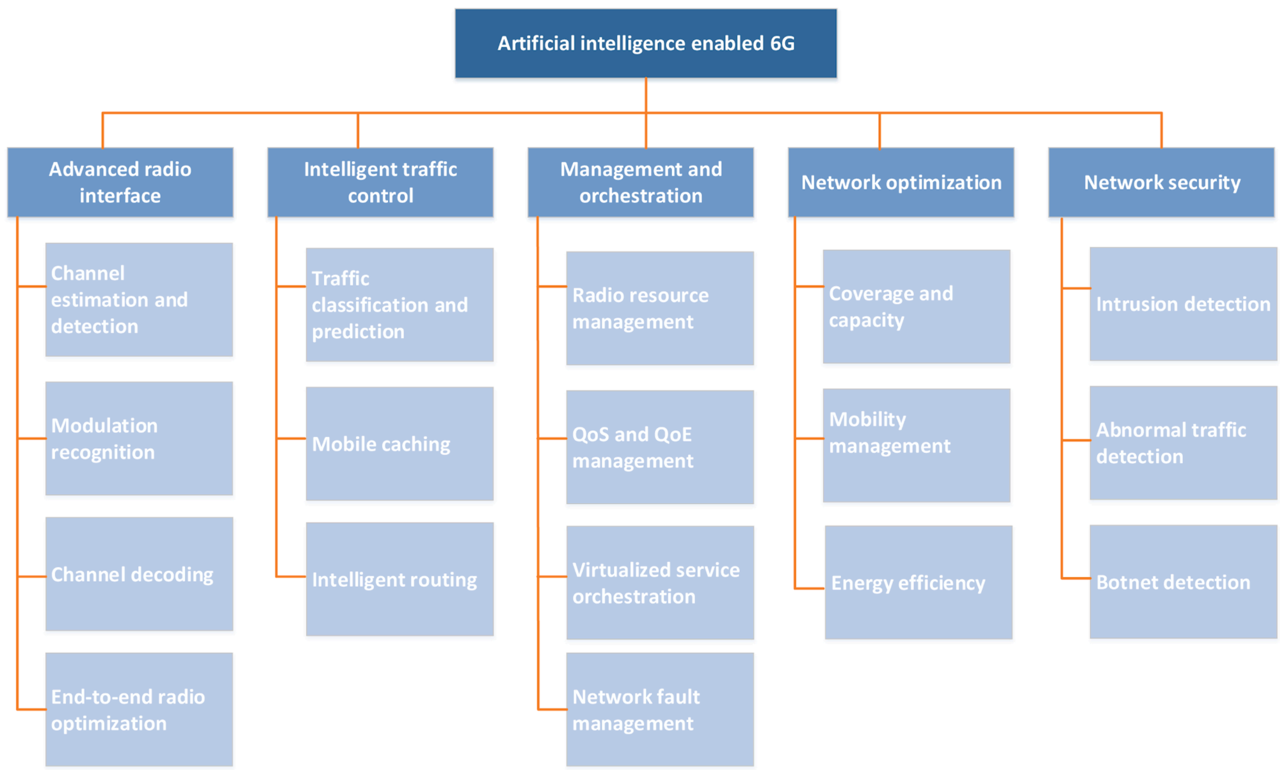

Fig. 4. An overview of applying AI to network towards 6G.

robustness of ML models, several works have been devoted to improving the modulation recognition accuracy and efficiency. For example, Nandi *et al.* [117] proposed a NN based modulation classifier to discriminate noise-corrupted modulated signals from several digital and analog modulation schemes. The experiment results show that the performance heavily depends on the manually extracted features. To overcome the weakness, DL approaches have been considered to learn essential features from raw data automatically[118]. proposed a CNN-based method to learn modulation types from sampled raw data over the radio interface. Test results show that the CNN-based approach outperforms two other conventional approaches, and the performance improves with an increased signal-to-noise ratio (SNR). However, the performance can not be improved continually at very high SNR because the short-term nature of training samples confuses the classifier. To overcome the issue, [119], developed a DL-based automatic modulation classification framework by leveraging the strength of the LSTM. After training the framework with 11 typical modulation types, the high performance is demonstrated at high SNR environments. Moreover, [120] investigated the performance of different DL algorithms including traditional CNN, ResNet, Inception CNN and LSTM on modulation recognition. The comparison results suggest that LSTM can achieve the highest accuracy in most situations. The existing works reveal the potentiality of DL in essential feature recognition. Therefore, it is worthwhile to exploit DL for recognizing other radio parameters such as channel coding, extracting CSI, and learning radio characteristics from signals.

5.1.3. Channel decoding

Since it is straightforward of applying NN to channel decoding, many ML-based decoders have been proposed since the 1990s. In contrast to conventional decoders based on information theory, the NN based decoders do not rely on expert knowledge. After the training process, the decoding process is simple and fast. However, a fundamental drawback of the NN-based decoder is the scalability because the training complexity grows exponentially with the increase of block length. Therefore, recent works turn to DL to address the issue of dimensionality by unfolding the interactive structure to layered structure[121]. proposed a decoder based on fully connected DNN to improve the performance of belief propagation (BP) in decoding high-density parity check (HDPC) codes. The results demonstrate that the decoder outperforms the conventional BP decoder algorithms although the performance degrades on large BCH codes. In [122], a BP decoder based on RNN is proposed by feeding the output of parity layers into the input of variable layers and unifying the weight parameters in each iteration. It is reported that the BP-RNN decoder outperforms plain BP decoder. Besides, [123] developed a decoder based plain DNN architecture to decode codewords of length N with K information bits. The decoder works for 16-bit length polar codes and achieves maximum posteriori performance. However, the performance degrades with the increasing length of information. Fortunately, when decoding structured codes, it can generalize a subset of codewords for training to decode unseen codewords. Moreover, the performance of the polar code can be improved by employing DL based decoding methods [124]. Specifically, the main idea is replacing sub-blocks of the decoder by the neural network (NN) based components, the resulting decoding approach enables a high level of parallelization and shows a competitive bit error rate (BER) performance. The existing studies reveal that applying DL to learn a structured-based decoding network is promising.

5.1.4. End-to-end radio optimization

Although ML approaches have been employed to improve the performance of certain processing blocks of the radio interface, the global optimum communication system can not be guaranteed by optimizing each block independently. Recently, some researchers re-reconsider the communication system as an end-to-end reconstruction task to optimize system performance[66],[125],[126]. In [66], the AE framework is used to represent the entire communication system with the transmitter, receiver, and AWGN channel. The system performance is optimized from an end-to-end perspective. Specifically, the transmitter and receiver are modeled as fully connected DNN, and the AWGN channel is represented as a noise layer. Therefore the communication system can be represented as an autoencoder system, which can be trained to optimize end-to-end performance such as BER. Simulation results indicate that the AE based approach can achieve better performance than the conventional BPSK with hamming code. Similarly, Kim *et al.* [125] proposed another AE based wireless communication, where the input data is encoded to a signal via a DNN at the transmitter side and the receiver decodes the received signal through the DNN. In [127],the AE based approach is extended to MIMO channels. Both the open-loop systems without CSI feedback and closed-loop with CSI feedback are considered. The simulation result of a 2 x 2 MIMO system indicates that the AE framework outperforms conventional open-loop MIMO schemes. The MIMO AE with perfect CSI outperforms the conventional precoding schemes at most SNR. In contrast, Huang *et al.* [128] employed the DNN for approximating the non-orthogonal multiple access (NOMA) system which is regarded as a black box. The whole NOMA system is formulated as an AE, where the encoding and decoding procedures are jointly processed. The simulation results demonstrate that the proposed solution achieves lower BLER than conventional hard decision methods. Furthermore, [126] proposed an end-to-end communication system by combining DNN and GAN. Specifically, a channel-agnostic learning system is developed by learning the communication channel output through a conditional generative adversarial network (GAN). The results demonstrate that the method is effective on Rayleigh fading channels and additive white Gaussian noise (AWGN) channels. These studies open a potential opportunity for building data-driven 6G communication systems.

Table 1 summarizes existing works on ML enabled intelligent radio interface.

5.2. Intelligent traffic control

5.2.1. Traffic classification and prediction

Traffic classification aims to identify and categorize specific applications or protocols from a large volume of traffic passing through networks. It is the basis for other important tasks such as traffic control, QoS and charging control, etc. With increasing encrypted traffic on the mobile network, the conventional deep packet inspection based traffic classification approaches face a great challenge. Recently, many efforts attempt to leverage the advanced ML approach for traffic classification and prediction. Wang *et al.* [129] proposed a stacked auto-encoder (SAE) based method to identify the upper layer protocols from a dataset of TCP traffic, the experiment result demonstrates that the method can achieve good precision and low recall rates. To classify encrypted traffic, [130] proposed a one-dimensional CNN based framework, which can model sequential data with low complexity. Targeted to a similar problem, [131] proposed a CNN based approach to realize encrypted traffic classification. The method can significantly reduce the effort on feature engineering and achieve high accuracy. Recently, Aceto *et al.* [132] investigated several DL methods such as MLP, CNN, and LSTM on encrypted mobile data traffic classification. It is demonstrated that DNN can automatically extract complex features from large amounts of mobile data traffic. Experiment results reveal that DL based approaches outperform ML methods in terms of accuracy.

Moreover, ML techniques have been widely used to predict future traffic distribution. To understand the traffic demand patterns of the wireless mesh networks, [133] precisely estimated traffic distributions by employing DBN with Gaussian models[134]. proposed a method to model the spatial and temporal correlations of mobile traffic by combining AE and LSTM. Specifically, AE is used to extract the spatial feature, reduce dimension, and train parallelism. Compressed representations generated by AEs are processed by LSTM to forecast future

Table 1
A summary of major works on ML/DL based radio interface design.

Domain	Ref.	Target Problem	Model	Learning paradigm	Main contribution
	[112]	Channel estimation for OFDM system	DNN	supervised	Achieve better performance with fewer overheads
	[113]	Lightweight channel estimator	CNN	supervised	Exceeds existing estimators with low complexity
Channel	[114]	Channel estimation of M-MIMO	DNN	supervised	Realize channel estimation with low BER
estimation	[116]	Channel detection	DL	unsupervised	Achieves similar detection accuracy with less time
detection	[64]	Channel detection without models	CNN ,RNN	unsupervised	Exceeds conventional channel detectors
	[117]	Discriminate noise-corrupted signals	NN	supervised	Propose a NN based modulation classifier
Modulation	[118]	Learn modulation from raw data	CNN	supervised	CNN-based modulation recognition approach
recognition	[119]	Automatic modulation classification	LSTM ,CNN	unsupervised	LSTM-based automatic modulation classification
	[120]	Modulation recognition	ResNet LSTM	unsupervised	LSTM exceeds other DL based approaches
	[121]	Improve BP in decoding HDPC	DNN	unsupervised	DNN-based decoder exceeds conventional BP decoder
Channel	[122]	Improve performance of BP decoder	RNN	unsupervised	BP-RNN decoder outperforms BP decoder
coding	[123]	Decode polar code and random code	DNN	unsupervised	Propose a plain DNN based decoder
	[124]	Decode polar codes	DNN	unsupervised	DNN based method achieve shorter decoding latency
	[66]	Optimize the E2E communication system	AE DNN	unsupervised	AE framework to optimize wireless communication
End-to-end	[125]	Optimize the E2E communication system	AE DNN	unsupervised	AE based approach to optimize wireless system
radio design	[127]	Optimize the MIMO communication system	AE NN	unsupervised	AE method outperforms open-loop MIMO schemes
	[128]	optimize the NOMA communication system	DNN AE	unsupervised	The solution achieves lower BER than existing methods

traffic demand, experiment results demonstrate the method outperforms conventional approaches like SVM. Moreover, to realize mobile traffic forecast in long time frames,[135] developed a Spatio-temporal NN to capture Spatio-temporal features of mobile traffic by combining LSTM and 3D CNN. By combining the predictions with historical means, they significantly extended the time frame of reliable prediction. Similarly, [136] employed CNN and LSTM to perform mobile data traffic prediction. Thanks to the effective Spatio-temporal feature extracting capability, the proposal significantly outperforms conventional approaches in terms of prediction accuracy. Existing studies reveal that the complex Spatio-temporal correlations inside of mobile traffic can be effectively learned by CNNs and RNNs, which are good at modeling spatial and temporal correlated data traffic. LSTM is an effective approach to forecast traffic demand based on learned Spatio-temporal correlations.

5.2.2. *Traffic caching*

The increasing popularity of enhanced mobile broadband applications such as AR, VR, XR results in the exponential growth of mobile data traffic. Meanwhile, some mission-critical IoT applications such as autonomous vehicles require ultra-low latency. To address these challenges, mobile edge computing emerges as a new paradigm. However, it is very challenging to find optimal caching strategies include optimized cache placement, cache update, and content popularity analytics. DL can play an important role in the design of efficient mobile edge caching and computing mechanisms. For example, to maximize the gain of proactive caching in the context of Device-To-Device (D2D) networks, [137] employed the K-means to cluster users and determine the set of influential users to cache local popular content. In [138], the author proposed a transfer learning-based solution to learn a model that can smartly cache contents in the base station (BS). Besides, to optimize the caching in small cell networks, [139] employed a clustering algorithm to group users with similar content preferences, then the RL is applied for BSs to optimize caching decisions. Similarly, Pang *et al.*[140] developed a DL based solutions for BS to learn user request patterns and make optimal caching decisions, and proposed a cooperation strategy for nearby BSs to serve user request collectively. Experiment results show significant gains in terms of latency reduction and traffic saving. Moreover, Jiang *et al.* [141] developed a distributed deep Q-learning based caching solution to improve the edge caching efficiency. Specifically, based on the predicted user preference and content popularity, the deep Q-learning approach is used to find the optimal caching strategy. Simulation results demonstrate that the method outperforms the existing algorithm in terms of the cache hit rate. Moreover, to tackle the problem of joint edge computing and caching for the Internet of Vehicles (IoV), Dai *et al.*[142] developed an intelligent resource allocation approach by utilizing DRL. Numerical results verify the effectiveness of the proposed solution.

In essence, DL techniques can enhance the mobile edge caching from several perspectives. First, they can be used to predict users' content request distribution and frequency, and mobility pattern, which can be used to optimize cache contents store and replacement policy. Furthermore, they can be used to learn users' interests, activities, and interactions, which can be helpful to improve the prediction accuracy of future user behaviors. Moreover, they can be used to classify users based on their activities, which is valuable to determine which content to store. Meanwhile, combining DL with mobile edge caching faces many challenges. The data processing should be able to extract useful data from a large amount of content in different formats to train DNN models.

5.2.3. *Intelligent routing*

To fulfill diverse QoS requirements 6G applications by efficiently utilizing limited network resources, numerous heuristic algorithms have been developed to optimize routing performance with complex constraints. The major shortcoming of heuristic algorithms is computational complexity. Recently, some researchers have employed the ML approach to solving routing issues. ML-based routing algorithms can make near-optimal routing decisions quickly once trained. Moreover, ML algorithms do not depend on an accurate mathematical network model, which makes it appealing for complex 6G network scenarios. From the literature, it can be found that supervised learning and RL are usually considered in routing optimization. In supervised learning-based algorithms, network and traffic state are often used as the input, and the output is the routing decision of the heuristic algorithm. For example, [143] proposed a routing framework with an ML-based meta-layer, which uses the input and output of the heuristic algorithm as the training dataset. Experiment result indicates the approach can achieve heuristic-like performance in real-time. Moreover, [144] proposed a dynamic routing mechanism named as NeuRoute. Specifically, LSTM is used to predict future network traffic demands. The network states and the predicted traffic demands are used as input and the routing decisions from heuristic algorithms are used as an output to train a neural network model. The routing mechanism can achieve results comparable to the heuristic algorithm in real-time after training. Although supervised learning based routing solutions can achieve performance comparable to heuristic algorithms in real-time, generation a large amount of labeled training dataset results in high computational complexity.

As an alternative approach, RL can be used to optimize routing. The author in [145] developed an RL based routing mechanism for Software-defined networking (SDN). The mechanism can select near-optimal traffic routing paths based on the dynamic network status. Similarly, [146] proposed a logically centralized routing mechanism by using the random neural network and RL for the SDN-based inter-data center overlay network, the experiment results demonstrate the mechanism works well even in very dynamic environments. Moreover, to meet different QoS requirements of diverse applications, [147] proposed a QoS aware routing mechanism for SDN by leveraging RL. Specifically, By using the maximum QoS as a reward, the RL based routing mechanism can select the best path according to traffic types and user requirements. Similarly, [148] developed a DRL based routing solution to minimize the end-to-end network delay. Recently, Mao *et al.* [149] proposed an intelligent next routing node selection mechanism based on DBN and developed a software-defined router. By combining the open shortest path first routing strategy, the proposed methods can achieve higher throughput with much less signaling overhead. Generally speaking, in the RL framework, the SDN controller or router acts as the agent and the network system is the environment, which contains different network and traffic states. The action is the routing decision in each hop. Various rewards can be defined based on optimization targets such as delay, link utilization, congestion, etc.

Table 2 summarizes major works on ML/DL enabled intelligent traffic control.

5.3. *Network management and orchestration*

5.3.1. *Radio resource management*

Traditionally, radio resource scheduling problems are solved by optimization, heuristic, and game theoretic-based approaches. However, the networks evolving towards 6G become increasingly complex, it is very challenging to formulate an accurate mathematic model and solve the large-scale problem to get global optimal results in a short time. Therefore, ML is explored as an alternative solution. The authors in [150] proposed a radio resource management framework based on RL. The framework includes a centralized learner who makes decisions based on reported information from distributed actors that collect experienced information from the network and enforce the learned policies from the learner. To reduce packet delay and packet-drop rate, [151] proposed an approach to optimize radio resource scheduling based on RL combined with NN and evaluated the performance of five different RL algorithms with different parameters, traffic classes, and optimization objectives. Recently, to solve the challenging issue of radio resource scheduling in Radio Access Network (RAN) slicing, [152] proposed an intelligent radio resource scheduling approach based on a

Table 2
A summary of existing works on ML/DL enabled intelligent traffic control.

Domain	Ref.	Target Problem	Model	Learning paradigm	Main contribution
	[129]	Identify protocols from TCP traffic	SAE	un-supervised	The method achieves good precision rates
Traffic	[130]	Classify encrypted traffic	1D CNN	supervised	CNN based method to classify encrypted traffic
classifi-	[131]	Classify encrypted traffic	CNN	supervised	Traffic characterization and application identification
cation	[132]	DL performance on traffic classification	MLP, ,LSTM	un-supervised	DL approaches outperform RL methods in accuracy
	[133]	Wireless network traffic prediction	DBN	supervised	Consider long-term dependency and short-term fluctuations
Traffic	[134]	Forecast protocols from TCP traffic	AE+ LSTM	un-supervised	Use AE and LSTM to model traffic correlation
prediction	[135]	Forecast long term traffic	3D-CNN +LSTM	supervised	Significantly extends prediction time frame
	[136]	Forecast mobile traffic	LSTM+ 3D-CNN	un-supervised	ML method outperforms conventional approaches
	[137]	Determine influential users for caching	K-means	un-supervised	Use K-means to cluster and select influential users
	[138]	Smartly cache contents in BS	Transfer learning	un-supervised	Transfer learning solutions for smart caching
Traffic	[139]	Optimize caching in small cells	Cluster +LSTM	un-supervised	Use clustering to group users ,RL to optimize caching
caching	[141]	Improve edge caching efficiency	DQL+ 3D-CNN	NA	DQL approach to achieve optimal caching
	[140]	Optimize caching in BS	LSTM	un-supervised	The LSTM method achieves latency and traffic saving
	[142]	Joint computing and caching optimization	DRL	NA	DRL framework efficiently orchestrates caching
	[143]	Routing optimization	NN	supervised	Framework with ML-based meta layer obtains heuristic routing
	[144]	Routing optimization	NN +LSTM	supervised	Transfer learning based solutions for smart cache
	[145]	Routing optimization in SDN networks	RL	NA	RL based approach can select near-optimal routing
Intelligent	[146]	Routing for inter-DC SDN	NN+ RL	NA	RL based approach works in highly chaotic environments
routing	[147]	Routing optimization in SDN	RL	NA	RL method enables time-efficient and QoS aware routing
	[148]	Routing and caching optimization	DRL	NA	DRL approach achieves optimal routing with minimal E2E delay
	[149]	Optimal next routing node selection	DBN	un-supervised	Software defined router achieves throughput with less overhead

collaborative learning framework that combines the DL with RL. Specifically, the DL is used to perform offline resource allocation in a large time-scale and RL is used to perform online resource scheduling on the small time-scale. Moreover, to realize optimal resource allocation in ultra-dense networks, [153] proposed a collaborative deep Q-learning method to perform user-cell association. The small-cells selected by users and local information are used as input to the NN. The output is the estimated Q-values, which can be used by users to select a small-cell. Furthermore, the distributed devices pose a big challenge to the resource management of future networks with D2D communication. To this end, an RL based on the Bayesian network (BN) is applied to maximize the system throughput of D2D networks subject to the power constraints of devices [154]. Devices establish coalitions by considering BS selection, transmission power, and transmission mode to maximize the long-term rewards. Moreover, oriented to the radio resource allocation issues in the tactile Internet, [155] proposed a Q-learning algorithm to maximize the throughput of data-intensive users by strategic resource-block scheduling. By learning the traffic patterns and channel conditions of the network, the Q-learning framework can optimize the latency and throughput of data-intensive users by intelligent radio resource allocation.

5.3.2. QoS And QoE management

As 6G is expected to support various IoE applications, it is more challenging to manage the diverse QoS requirements from different applications and ensure the QoE of different users. Efficient QoS and QoE management are critical for the network operator to improve user satisfaction and reduce customer churn. QoS parameters are closely related to the key performance indicator(KPI) of networks such as transmission rate, queue length, etc. Deriving the complex quantitative correlations between QoS parameters and KPI is critical for managing QoS. To this end, [156] proposed a delay estimation approach by using NN. The traffic load and the routing policy is used as input, and the network delay is used as the output of the supervised learning approach. Experiment results show that the NN-based estimator outperforms the conventional M/M/1 model in terms of estimation accuracy. Similarly, [157] attempted to discover the mapping relations between QoS parameters and KPI metrics by using the decision tree. The linear regression algorithm M5Rules is used to discover the quantitative impact of KPI on QoS. The QoE is a subjective metric to quantify the satisfaction of uses to a specific service. It is quite time consuming to get the QoE values. Therefore, understanding how various QoS parameters affect the QoE values is especially important to derive QoE value quickly[158]. aims to estimate the QoE of video streaming service by a supervised learning approach. Network parameters including round trip time (RTT), jitter, bandwidth, and delay are used as input, and QoE is used as an output to train the NN model. Based on the estimated QoE, the SDN controller can tune network parameters to improve QoE. Similarly, Abar *et al.*[159] attempted to estimate QoE values from video quality parameters. Four ML algorithms including decision tree, neural network, K-NN, and random forest are investigated. Moreover, Pierucci *et al.* [160] investigated the relationship between QoE and QoS parameters to predict user's QoE based on parameters such as user throughput, numbers of active users, channel quality indicators by employing MLP. The simulation results demonstrate high prediction accuracy. With the introduction of new applications such as XR in 6G, new QoE and QoS evaluation metrics makes it more challenging to manage QoE and QoS, existing works reveal that DL is promising to the learn the complex relations between them to achieve more efficient QoE insurance and resource utilization.

5.3.3. Virtual service orchestration

The SDN and Network Function Virtualization (NFV) technologies enable more flexible network service provision, which is helpful to fulfill diverse service requirements. Meanwhile, it is challenging to achieve automated network services configuration, provision, and management. To this end, ML can be used to facilitate the automatic service provision and optimize resource orchestration of SDN and NFV based 6G networks. It is of great importance to use AI and big data technology in SDN and NFV based networks to achieve intelligent network management and optimization [161]. Zorzi *et al.* [162] proposed a novel framework named as COBANETS by combining the ML approach with the network virtualization paradigms. The new architecture can realize automatic optimization and reconfiguration. Recently, some works have been done to reduce service provision costs and improve resource utilization by using ML approaches, especially RL. For example, [163] employed the Markov decision process and Bayesian network method to optimize the dynamic resource allocation for VNFs. Moreover, to achieve efficient service provision,[164] employed RL to create service chains dynamically. Besides, to obtain optimal VNF assignment policy,[165] formulated the network function assignment issue as a two-stage Stackelberg game and applied the RL approach to solving the problem. Furthermore, the DL has been used to make intelligent resource orchestration in the context of network slicing. The researchers in [166], [167] employed DRL for resource management of network slices. The experiment results demonstrate that DRL is an effective approach to solve resource management issues of network slicing scenarios, such as core network slicing, radio resource slicing.

5.3.4. Network fault management

Fault management includes detection, prediction, diagnosis, and mitigation of abnormal status of networks. The advances in emerging technology such as NFV, SDN, network slicing, and new paradigms such as space-aerial-terrestrial-ocean integration make 6G more heterogeneous, complex, and dynamic. Efficient fault management is more challenging in 6G networks. Recently, ML techniques have been exploited to address these challenges for the vision of cognitive network management.

- **Fault detection**: Andrades *et al.* [168] proposed a SOM based method to detect faults in networks by analyzing measurements reported by UE. The evaluation results in two real Long Term Evolution (LTE) networks demonstrate that it can effectively diagnose and locate faults within the networks. Liao *et al.*[169] developed a framework based on principle component analysis (PCA) and fuzzy classification to detect anomalies in networks. Specifically, PCA is used to reduce the dimension of input data and a kernel-based semi-supervised fuzzy clustering is employed to classify samples. Results show that the solution can proactively detect anomalies associated with the various fault of LTE networks. Moreover, Adda *et al.* [170] developed a real-time fault detection and classification framework by using K-means, Fuzzy C-means, and expectation maximization (EM). The framework utilizes Simple Network Management Protocol (SNMP) to collect logs from various network devices. 12 features sensitive to the pattern of network traffic are selected, and different traffic patterns are used to form clusters represent different normal and abnormal network states. Evaluation results show that K-means is faster than Fuzzy C-means, which is more accurate. Furthermore, Hashmi *et al.* [171] investigated the performance of five different unsupervised learning algorithms on detecting faults in the networks, experiment results reveal that SOM outperforms Fuzzy C-means and K-means.
- **Fault prediction**: Although Bayes network (BN) has been widely used to predict faults in cellular networks, it is not sensitive to temporal factors. Therefore, Ding *et al.* [172] employed dynamic BN to model dynamic changes in network entities and dependencies among them. It is reported that the method is robust in fault prediction and fault localization. Recently, Kumar *et al.*[173] investigated the feasibility of regression and analytical ML methods to predict faults on a cellular network. Different models are compared based on time-stamped faults from a real network. The results show that DNN with AE outperforms other ML methods including autoregessive NN and SVM.
- **Fault diagnosis**: To realize automated fault diagnosis for mobile networks, Khanafer *et al.* [174] developed a model by employing BN. Causes and symptoms of faults are used as core elements of the model, alarms and KPI are considered as two typical symptoms. The authors verified the diagnosis model consisting of BN and entropy minimization discretization (EMD) in a real 3G network. Test results show that the method can diagnose the fault with an accuracy of 88.1%. Another fault diagnosis solution is presented in [175], the authors built a framework based on transfer learning (TL) to diagnose the fault in femtocells. To overcome the data scarcity issues of femtocell networks and improve the accuracy of general TL techniques, a new model named as cell-aware transfer (CAT) is proposed, where two classifiers are trained and used together in the diagnostic model. Experiment results show that the method outperforms SVM and TL-SVM in terms of diagnostic accuracy.

Table 3 summarizes major works on ML/DL enabled network management and orchestration.

5.4. Network optimization

5.4.1. Coverage and capacity

For future 6G networks, coverage and capacity optimization is critical to provide universal network services to various use cases. The conventional optimization approaches, such as linear or non-linear programming, dynamic programming, heuristic algorithm, game theory is not adequate to handle the large scale and dynamic network 6G scenarios. Therefore, many researchers have turned to ML techniques for more efficient and intelligent solutions. To achieve optimal coverage by tuning cluster size and antenna parameters, Debono [176] proposed a two-layered SOM based approach. Specifically, two SOM algorithms are employed to perform cluster optimization without and with antenna parameters tuning simultaneously. The results show the gain of 5% for only cluster optimization and 13% for both cluster and antenna parameter optimization[177]. developed an RL framework to achieve the coverage and capacity optimization by tuning the down-tilt angle of antennas. To realize a fully autonomous optimization process, the author investigated different learning strategies based on Fuzzy Q-Learning and proposed a cluster-based strategy. Similarly, Razavi *et al.* [178] proposed a fuzzy RL approach to optimize the coverage of LTE networks. Simulation results confirm that the solution can converge to global optimal settings. Besides, to mitigate the interference from micro-cell to macro-cell in self-organized femtocell networks, the authors [179] divided the problem into carrier optimization issue and power optimization issue. The former is solved by a Q-learning method. The investigation shows that the approach can optimize the setting of femtocells and mitigate their interference to the macrocells. Moreover, oriented to the issue of inter-cell inference coordination in the downlink of the LTE system, Dirani *et al.* [180] formulated it as a cooperative

Table 3
A summary of existing works on ML/DL based network management and orchestration.

Domain	Ref.	Target Problem	Model	Learning paradigm	Main contribution
	[150]	Estimate QoS from KPI data	RL	NA	RL based framework with learners and actors
Radio	[151]	Optimize radio resource scheduling	RL+ NN	NA	RL based framework to evaluate RL algorithms
resource	[152]	Optimize resource for RAN slice	DL+ RL	NA	Combining DL and RL to perform resource allocation
mgmt.	[153]	Optimal resource allocation in DUN	RL+ NN	NA	RL based approach to perform user-cell association
	[154]	Optimize resource management for D2D	RL+ BN	NA	RL framework to maximize D2D throughput with power constraint
	[155]	Resource allocation in tactile Internet	RL	NA	Use QL to maximize throughput by strategic scheduling
	[156]	Derive QoS and KPI correlations	NN	supervised	Propose a NN based delay estimation
QoE and	[157]	Discover QoS and KPI correlations	DT	supervised	Using DT to discover mapping between QoS and KPI
QoS	[158]	Estimate video QoE from QoS	NN	supervised	Use NN to estimate QoE from video parameters
mgmt.	[159]	Estimate QoE from video parameters	DT,NN K-NN,RF	supervised	Investigate the performance of ML algorithms on QoE estimation
	[160]	Discover QoS and QoE correlations	MLP	supervised	MLP based approach to predict QoE based on QoS parameters
	[162]	Automatic virtual resource optimization	RL	NA	A framework to realize automatic resource orchestration
Virtual	[163]	Optimize resource allocation for VNFs	MDP+ BN	NA	MDP based framework to optimize resource for VNFs
service	[164]	Efficient virtual service provision	RL	NA	RL based framework to manage service chains
orches	[165]	Find optimal VNF assignment policy	RL+	NA	RL based approach for QoE estimation

Table 3 (*continued*)

Domain	Ref.	Target Problem	Model	Learning paradigm	Main contribution
	[167]	Optimal slice resource management	DRL	NA	DRL is effective to orchestrate sliced network resource
	[168]	Detect fault in LTE network	SOM	un-supervised	The SOM based approach can locate network faults
	[169]	Anomaly Detection	PCA+ fuzzy	semi-supervised	PCA and fuzzy classification can detect network anomalies
Network	[170]	Real-time fault detection	K-means+ FCM+EM	un-supervised	Real-time fault detection based on K-means, FCM and EM
fault	[171]	Network fault detection	SOM, FCM EM	un-supervised	Evaluate unsupervised learning algorithms on fault detection
mgmt	[172]	Predict faults in cellular networks	dynamic BN	supervised	The dynamic BN based method is robust in fault prediction
	[173]	Predict faults in cellular networks	BN,DNN AE,SVM	supervised	Investigate several ML methods to predict network fault
	[174]	Fault diagnosis for UMTS networks	BN+ EMD	supervised	BN and EMD based method can diagnose fault effectively
	[175]	Diagnose fault in femtocell networks	modified TL	supervised	CAT based method outperforms TL-SVM in diagnosis accuracy

multi-agent control problem and get the optimum result by applying the Q-learning framework, where the state is defined by transmitting power, spectral efficiency, the actions include power control, and the mean throughput is defined as rewards.

5.4.2. Mobility management

Mobility management for 6G is very challenging because 6G networks will be super heterogeneous, multi-layer, large-dimensional, and highly dynamic. To ensure user experience, improve resource utilization, and reduce the signaling overhead of networks, intelligent mobility management by learning and predicting user's movement and optimizing handover parameters is of great importance. Many researchers have attempted to understand user mobility behavior and predict the user's movement by ML techniques. For example, to predict the next cell a user will move in, the back-propagation NN is used in [181], the basic idea is to learn the mobility model of users, then make predictions of the next cell the user is most likely to move into. Similarly, to represent cell transitions and determine a user's trajectory, Mohamed *et al.* [182] formulated the problem by a discrete-time Markov chain. The approach does not require the training process and the optimization can be performed online. Results show that the solution can effectively predict the user's trajectory, the accuracy depends on the confidence parameter. Moreover, Si *et al.* [183] modeled the mobile network as a state-transition graph and formulated the problem by HMM and

Table 4
A summary of existing works on ML/DL based network optimization.

Domain	Ref.	Target Problem	Model	Learning paradigm	Main contribution
	[176]	Coverage optimization	SOM	unsupervised	Use SOM to achieve optimal coverage by cluster optimization
	[177]	Optimize coverage and capacity	RL	NA	Propose a RL based method realize coverage optimization
Coverage	[178]	Coverage optimization	fuzzy RL	NA	A fuzzy RL based method realize LTE coverage optimization
capacity	[179]	Optimize carrier and power	Q-learning	NA	Use Q-learning to mitigate interference in femtocell networks
	[180]	Interference coordination	Q-learning	NA	Use Q-learning to achieve inter-cell inference coordination
	[182]	Predict a user's trajectory	Markov chain	unsupervised	Develop a Markov process to Predict user's trajectory
	[183]	Predict user location	HMM	unsupervised	Use HMM to predict user's location
	[184]	Predict user location	discrete Markov	semi-supervised	Achieve good prediction accuracy with less labeled data
Mobility	[185]	User trajectory prediction	RNN	supervised	use RNN and GRU to predict user trajectory
mgmt.	[186]	User trajectory prediction	LSTM	supervised	Use LSTM to predict city level user trajectory
	[187]	HO parameters optimization	XSOM networks	unsupervised	Use SOM to optimize HO parameters hysteresis and TTT
	[188]	Mobility optimization	distributed QL	NA	QL based framework to adjust HO setting by mobility changes
	[190]	HO optimization	NN	unsupervised	NN based solution to determine the cell for handover
	[191]	Energy efficiency optimization	Q-learning	NA	QL based solution can achieve energy saving
	[192]	Improve EE of femtocells	Distributed Q-learning	NA	a Q-learning based solution to Improve EE while ensuring QoS
Energy	[193]	Maximize energy efficiency of UE	Q-learning	NA	The energy-efficient resource allocation by Q-learning
efficiency	[194]	Improve EE of network	Q-learning	NA	Optimize BS operation by QL without enough labeled data
	[195]	Optimize the EE of UDN	ML	supervised	The RL framework improves throughput without comprising EE
	[196]	Energy efficiency optimization	actor-critic RL	NA	Model free-RL approach to realize energy-aware resource allocation

attempted to make predictions about user location by learning mobility parameters. Three different scenarios verified the efficiency and accuracy of the HMM-based method. In contrast, [184] attempted to perform location prediction by using semi-supervised learning techniques to reduce the effort of generating labeled data. The authors built a discrete Markov model, then both labels and unlabeled data are used to train the model. Results demonstrate that the approach can achieve a reasonable accuracy even without a large amount of labeled data. Recently, [185] employed a DL approach to perform user trajectory prediction, a framework by sharing representations learned by Gated Recurrent Unit (GRU) and RNN is proposed to perform social network learning and mobile trajectories modeling. Furthermore, the mobility behavior prediction on a large scale is investigated in [186]. The authors employed the LSTM networks to model and predict the city-level movement patterns of a large group of people. The result demonstrates better prediction accuracy than conventional LSTM.

Besides, the handover (HO) parameter optimization is another important topic for 6G networks because it can affect many aspects including coverage capacity, energy consumption, interference, and user experience. Therefore, several works by leveraging ML have been devoted to the issue. For example, to optimize HO parameters like hysteresis and time to trigger, Sinclair *et al.* [187] developed a method based on a modified version of SOM, which can achieve a balance between unnecessary HO and call drop rate. Experiment results show the method can reduce dropped calls and unnecessary HOs by up to 70%. In [188], Mwanje *et al.* proposed a distributed Q-learning framework to realize mobility robustness optimization (MRO). Based on the mobility behavior observed in each cell, the framework takes a certain action and receives rewards or penalties. The method makes it possible to adjust the HO setting automatically according to mobility changes in the network. Similarly, Q-learning is employed in [189] to achieve mobility load-balancing besides MRO. Another HO optimization solution is proposed in [190]. The authors employed two NN to determine the best target cell a user should handover to based on the perceived QoE of the users.

5.4.3. *Energy efficiency*

Besides conventional energy efficiency optimization approaches, the ML technologies have been investigated for the energy saving of mobile networks. Kong *et al.* [191] developed a solution based Q-learning to dynamically switch on/off modular resources based on dynamic network traffic conditions. It is reported that the solution can achieve an energy-saving gain of 80% without compromising service blocking probability. Similarly, [192] proposed a distributed Q-learning approach to reduce the energy consumption of two-tier femtocell networks with QoS assurance. In contrast, to maximize the energy efficiency of UE while minimizing inter-tier interference of a heterogeneous cloud radio access network, [193] developed an energy-efficient resource allocation scheme based on Q-learning framework to practically model the objectives and system specifications. Recently, to improve the energy usage of small cells with energy harvesting, Miozzo. *et al.* [194] proposed another solution by using Q-learning to determine which BSs to turn on/off. Similarly, to optimize the energy efficiency of ultra-dense radio networks, [195] employed supervised learning and big data processing techniques. The experiment result shows that the solution can improve throughput and energy efficiency by 50% and 135%

respectively than conventional approaches without comprising energy efficiency. Given the stochastic nature of the wireless channel and green energy environment, a model free-learning algorithm is more appealing. The authors [196] proposed an actor-critic based RL approach to realize energy-aware resource allocation by optimizing the number of users associated with each BS, power allocated to each user, and the energy source of BS. Numerical results demonstrate the convergence property and energy efficiency of the proposed algorithm. Furthermore, Vodafone partnered with Ericsson initiated activities to reduce the energy consumption of commercial mobile networks by using ML [197]. Specifically, an ML algorithm is trained with site-specific data to learn the patterns of local activity and traffic patterns to intelligently manage the sleep mode of BS. Field experiments report that the ML-based approach can achieve 15 percent energy saving without comprising consumer experience.

Table 3 summarizes major works on ML/DL enabled network optimization from different perspectives.

5.5. Network security

With the uprising of new attacks, 6G networks will face various new challenges and security threats. Typically, the network security systems should at least include firewalls, intrusion detection systems (IDS), and antivirus functions. IDS can be used to identify unauthorized access, malicious behaviors such as destruction, modification, etc. Three types of analytics approach can be used to realize IDS: anomaly-based, signature-based, and hybrid. Signature-based techniques identify potential attacks by using signatures of those attacks. They are only effective in detecting attacks with known signatures. Therefore, frequent updates of the signature database of attacks are required, which makes it impossible to detect new attacks. Anomaly-based approaches establish the knowledge database of normal network and system behavior and then identifies the deviations from normal behavior as anomalies. The data of abnormal behavior can be used to develop signatures for the signature-based approach. The main drawback of the approach is the possible high false alarm rate due to unknown legitimate system behaviors. The hybrid approach combines the signature and anomaly detection to improve the rate of know intrusions and reduce the false-positive rate of unknown attacks [198]. Existing IDSs are usually separately deployed within certain areas, which makes them hard to cooperate. To overcome the limitation of conventional IDS, ML techniques have been widely used in modern network security systems for intrusion detection [79].

5.5.1. Intrusion detection based on ML

- **KNN**: Sharifi *et al.* [199] developed an IDS by combining KNN and K-Means. The principal component analysis (PCA) is employed to select important features from input data, then the K-means algorithm is used to cluster input data. Finally, the KNN is to used to classify the clustered dataset. However, the average classification accuracy of the experiment on the NSL-KDD dataset is only about 90%. Similarly, to improve the classification performance of KNN for intrusion detection, Shapoorifard *et al.* [200] introduced the farthest neighbor and nearest-neighbor techniques. Experiment results based on the NSL-KDD dataset demonstrate that the approach can achieve better performance in terms of detection rate, classification accuracy, and failure alarm rate. Moreover, Vishwakarma *et al.* [201] proposed an intrusion detection method by combining KNN and Ant Colony Optimization (ACO) algorithm. The input dataset is pre-trained by using the ACO, and KNN is used to classify the dataset. The overall accuracy is 94.17%, and the FAR is 5.82%. Unfortunately, the dataset used for the experiment includes very limited samples.
- **SVM**: Li *et al.* [202] developed a signature-based approach by using an SVM classifier with a radial basis function (RBF) as the kernel to classify the known security attacks into predefined categories. To minimize the bias in the KDD set and maximize classifier generalization, ACO is used to select a subset of the training dataset. The cross-validation results show that the approach can achieve an overall 98% accuracy with unknown variance. In addition, Hu *et al.* [203] proposed an anomaly classifier based on robust SVM. The study reported a 75% accuracy rate without false alarms and 100% accuracy with 3% false alarms. Shon *et al.* [204] developed a framework for detecting novel attacks based on a combination of SVM, SOM, and GA. The enhanced SVM shows an accuracy of 87% with an FP rate of 10.20% and an FN rate of 27%, which are much better than those from the conventional SVMs.
- **Decision tree**: Kruegel *et al.* [205] enhanced the Snort [206] by using decision tree as the signature detection engine. They derived a decision tree based on a variant of the ID3 algorithm to pick the most discriminating features of the ruleset, which makes it possible for parallel evaluation of features. To detect malicious activity, [207] developed a network security system named EXPOSURE, which consists of five major components: data collector, feature attribution, malicious domain collector, learning, and classifier. The classifier components of the system are based on the C4.5 algorithm which can generate pruned or unpruned decision trees. Cross-validation tests demonstrate a detection accuracy of malicious domains was 98.5% with the false alarm rate (FAR) of 0.9%.
- **Naive Bayes**: Panda *et al.* [208] developed a misuse based intrusion detection framework by employing the naive Bayes classifier. By training and testing with KDD 1999 dataset, the classifier can detect four types of predefined attacks achieve with around 90% accuracy and 3% of the cumulative FAR. Similarly, [209] proposed a naive Bayes classifier based on a simplified form of Bayesian network, where the root node and leafs representing attributes compose the naive Bayes classifier structure. The anomaly detection experiment demonstrates 98% accuracy for the normal category and 89% for the abnormal category.
- **HMM**: To detect the attacks on web applications, Ariu *et al.* [210] developed a system named HMMPayl by using HMM to extract the signatures of attacks. The system examines the HTTP payload by using N-grams [211] and builds a multi-classifier by employing multiple HMMs. HMMPayl can achieve an accuracy higher than 85% with an FP rate of around 10^{-3}. Besides, [212] proposed an intrusion detection framework by using HMM with 5 states and 6 observation symbols per state. The Baum-Welch method is employed to determine the hidden parameters. The test result shows an accuracy of 79%.

5.5.2. Intrusion detection based on DL

In contrast with conventional ML, DL makes it possible for the cybersecurity system to automatically learn signatures from experience and detect future intrusions based on learned information. Moreover, it helps to identify patterns that are differed from known normal behavior, which makes it possible to identify unknown intrusions. In recent years, DL is attracting more attention from academia and industry, DL is increasingly used in the modern cybersecurity system [213].

- **Deep belief network**: Li *et al.* [214] employed the DBN for anomaly detection. Specifically, AE is used to reduce the dimensionality of the dataset. Unsupervised training is performed on RBM, then the output is fed to the back-propagation NN for classification. The experiment results show an accuracy of 92.10%, FP of 1.58%, and TP of 92.20%. Moreover, [215] proposed an intrusion detection approach by using DBN and probabilistic neural networks (PNN). The nonlinear learning capability of DBN is used to convert original data to low dimensional data without losing essential features, then PNN is used to classify low-dimensional data. The experiment results show a remarkable accuracy of 99% with the FAR of 0.6%.

- **Auto-encoder**: To identify attacks and threats in Wi-Fi networks, Thing *et al.* [216] employed a stacked auto-encoder (SAE) framework to categorize the test network traffic with an accuracy of 99.86%. Similarly, Feng *et al.* [217] applied deep-structure AE neural networks to detect abnormal spectrum usage in radio networks, the time-frequency diagram is used as the feature of the model. Experiments reveal remarkable detection accuracy thanks to the depth of AEs.
- **Recurrent neural network**: Yin *et al.* [218] proposed an IDS based on RNN. The system supports both the binary classification and multi-class classification. The training accuracy of binary classification and multi-classification are 99.8% and 99.5% respectively, whereas the test accuracy of binary classification and multi-classification are only 83.3% and 81.2% respectively. Moreover, [219] developed an IDS by using LSTM classifier. The experiment results show that the LSTM classifier outperforms conventional static classifier. The classification accuracy rate can reach 93.8% with the FAR as 1.62%. In addition, Le *et al.* [220] investigated the performance of 6 widely used optimizers of LSTM based intrusion detection model. The study shows that the LSTM RNN model with Nadam optimizer can achieve an accuracy of 97.5% with the FAR of 9.98%, which outperforms prior arts.
- **Convolutional neural network**: Yu *et al.* [221] proposed a DL approach named as dilated convolutional AE to realize network intrusion detection. The approach combines the advantage of SAE and CNN to learn essential features from large amounts of unlabeled raw network traffic data automatically and efficiently. The performance evaluation of classification tasks shows the precision and recall were 98.44% and 98.40% respectively. Besides, Tang *et al.* [222] employed DNN for flow-based anomaly detection in SDNs. 6 features are extracted from traffic flows of the NSL-KDD dataset to evaluate the accuracy of anomaly detection. The approach can achieve a trade-off between the learning rate and classification accuracy.

5.5.3. Botnet detection

The botnet is another serious threat to mobile networks, especially in the case of massive IoE scenarios, where large numbers of simple devices under high risk of being hijacked. Efficiently detecting botnet is critical to 6G security. Due to increasing data traffic volume, many researchers have resorted to ML/DL for potential solutions. To extract the typical features of mobile botnet threats, Oulehla *et al.* [223] proposed a framework by employing NN. The experiment result demonstrates that the framework can effectively identify both client-server and hybrid botnets. Torres *et al.* [224]employed LSTM to extract traffic patterns of botnets through their life cycle. Particularly, under-sampling and over-sampling measures are employed to solve the traffic class imbalance between normal user traffic and botnet attack traffic. Moreover, the peer-to-peer botnet threats are investigated in [225], the experiment results show that the standard MLP based detection mechanism can achieve remarkable accuracy. Furthermore, to detect botnet attacks from massive IoT devices, McDermott *et al.* [226] developed a bidirectional LSTM model to identify four attack vectors of the Mirai botnet [227]. After training the model with created botnet traffic, the approach can detect different botnet attacks with accuracy ranging from 91.95% to 99.99%. However, it is only tested with known botnet traffic.

5.5.4. Malware detection

Various applications installed on mobile devices may steal and abuse the private information of mobile users. This means an increasing threat to security and privacy protection. Recently, DL has been exploited for detecting such threats from malware. Yuan employed RBM [228] to detect malware. By training the model with both labeled and unlabeled data from mobile APPs, the experiment results show the approach can achieve a remarkable classification accuracy of Android malware. Similarly, Su *et al.* [229] developed a framework by combining DBN and SVM. Specifically, DBN is used to extract essential features of Andriod malware, then SVM is employed to classify APPs based on extracted features. It is reported that the approach can achieve high accuracy at high speed. In addition, Chen *et al.* [230] enhanced the RBM based malware detection model by incorporating location information for feature extraction and classification. The experiments demonstrate the approach outperforms several other ML methods. Moreover, to overcome the limitations of signature-based approaches on detecting sophisticated Andriod malware, [231] employed an SAE based approach to analyze the graph generated during executing code routines. The framework can accurately detect Andriod malware that intentionally obfuscates and repackages to bypass signature-based detection. Moreover, Ding *et al.* [232] proposed a malware detection system by DBN. Unsupervised learning is used for DBNs to discover essential features. The experiment results show that the DBN can achieve an accuracy of up to 96%, which outperforms widely used ML techniques such as SVM, KNN, and DT. Wang *et al.* [233] proposed a method to classify malware traffic by using CNN. The method does not need expert-designed features but directly takes the raw traffic as input to the classifier. Experiment results show the classification accuracy of up to 99.4%.

Table 5 summarizes major works of applying ML/DL to cybersecurity. By reviewing the existing studies, we can find that hybrid models have been increasingly considered recently, and better performance can be achieved by combining different algorithms intelligently. The advent of DL makes if possible for end-to-end learning and handling large amounts of raw data without domain expert involvement. An increasing number of works investigate the performance of various algorithms and a few researchers start to address the practical value of new algorithms and models. However, the benchmark datasets are very limited and out of date, the new dataset from a practical network facilitating the cybersecurity research is impending. Furthermore, there is not a uniform evaluation metrics to compare different algorithms. Many works only use accuracy to assess the test result. Although some studies use multi-criteria evaluation, different metric combinations make it difficult to compare different approaches. Moreover, most of the research ignores the time complexity and the detection efficiency of the algorithm in practical networks.

6. Industry standardization and projects

6.1. Standardization initiatives

6.1.1. 3GPP

3GPP started the big data-based network intelligence from the 5G system. In January 2018, 3GPP SA WG2 approved the study of enablers for network automation of 5G [234]. The objective is to study the necessary data exposed to the network data analytics and the necessary output to support the following use cases: 1) Customized mobility management at UE level. 2) QoS assurance verification and Non-standardized QoS profile generation. 3) Dynamic traffic steering and split, traffic steering based on user behavior.4) Resource management based on traffic classification. As a result of the study, the network data analytics function (NWDAF) is formally introduced in 5G network architecture at R16 [235]. Fig. 5 illustrates the interaction between NWDAF and other network functions. The NWDAF represents a network analytics logical function. It can collect user context and network operation data from related network functions and provides analysis results to other network functions. For example, it provides network slice level data analytics to policy control function (PCF) for intelligent policy generation and assists network slice selection function (NSSF) for intelligent slice selection.

Besides, in September 2018, 3GPP RAN approved the project proposal of RAN-centric data collection and utilization [236]. The project focuses on the study of network automation and intelligence oriented massive wireless data collection and application. It addresses the following major items: 1) Identify wireless big data-related use cases and potential gains such as Self-Organizing Networks (SON), enhanced

Table 5
A summary of existing works on ML/DL based network security.

Domain	Ref.	Target Problem	Model	Learning paradigm	Main contribution
	[199]	Intrusion detection	KNN+ K-means	semi-supervised	Combine KNN and K-means to classify intrusion traffic
	[200]	Intrusion detection	KNN+ K-FN	supervised	Introduce K-FN into KNN method to improve detection accuracy
	[201]	Intrusion detection	KNN+ ACO	supervised	Combine KNN and ACO to achieve high detection accuracy
Intrusion	[202]	Misuse detection	SVM	supervised	A signature based IDS by SVM classifier with RBF kernel
detection	[204]	Hybrid detection	SVM+ SOM	supervised	detect novel attacks by combining SVM,SOM and GA
(ML based)	[205]	Misuse detection	DT	supervised	Enhances the Snort by using DT as the signature detection engine
	[208]	Misuse detection	Naive Bayes	supervised	Employ the naive Bayes classifier for intrusion detection
	[209]	Anomaly detection	BN	un-supervised	Anomaly detection by Naive Bayes classifier based on BN
	[212]	Anomaly detection	HMM	un-supervised	Propose an IDS framework by using HMM
	[214]	Anomaly detection	DBN+ AE	un-supervised	Combine DBN and AE to improve detection accuracy
	[215]	Intrusion detection	DBN+ PNN	supervised	Combine DBN and PNN to improve detection accuracy
	[216]	Anomaly detection in Wi-Fi networks	SAE	semi-supervised	Employ a SAE framework to classify network traffic
Intrusion	[217]	Detect abnormal spectrum usage	SAE	semi-supervised	develop a SAE based approach Detect abnormal
detection	[218]	Intrusion detection	RNN	supervised	RNN based IDS framework to classify intrusion traffic
(DL based)	[220]	Intrusion detection	LSTM	supervised	LSTM based classifier outperforms conventional static classifier
	[221]	Intrusion detection	CNN+ SAE	un-supervised	IDS framework by combining staked AE and CNN
	[222]	Anomaly detection in SDN networks	DNN	un-supervised	Develop flow-based anomaly detection by employing DNN
	[223]	Mobile botnet detection	NN	supervised	The approach can detect both client-server and hybrid botnet
Botnet	[224]		LSTM	supervised	

Table 5 (*continued*)

Domain	Ref.	Target Problem	Model	Learning paradigm	Main contribution
		botnet detection			Employ LSTM extract botnets' features through life cycle
detection	[225]	P2P botnet detection	MLP	supervised	The approach can detect P2P botnet with high accuracy
	[226]	botnet detection in IoT networks	LSTM	supervised	The approach can detect botnet of IoT devices with high accuracy
	[228]	Mobile malware detection	RBM	semi-supervised	RBM based method detects Android malware with remarkable accuracy
	[229]	Mobile malware detection	DBN+ SVM	semi supervised	Combine DBN and SVM to detect Android malware with high speed
Malware	[231]	Mobile malware detection	SAE	semi-supervised	The approach can accurately detect sophisticated Android malwares
detection	[230]	Malicious APP detection	RBM	supervised	Incorporate location information in RBM to improve detection accuracy
	[232]	Malware detection	DBN	un-supervised	Propose DBN based framework to detect malware traffic
	[233]	Malware detection	CNN	supervised	Propose a CNN based method to classify malware traffic

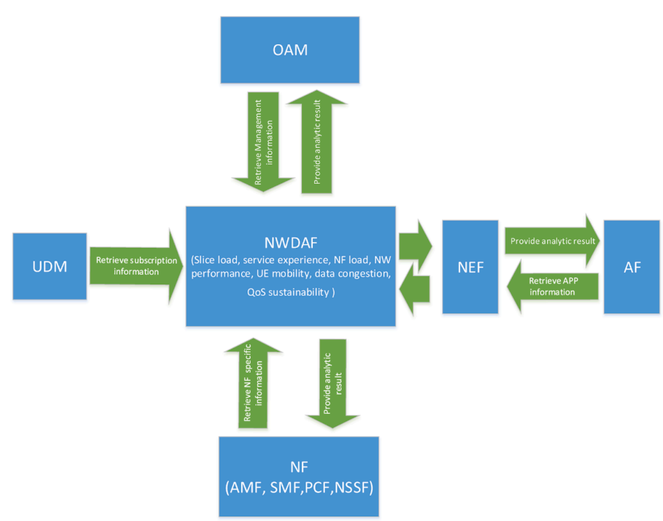

Fig. 5. Network architecture for data analytics.

URLLC, etc. 2) Study the potential impact of new use cases to existing specifications. For example, evaluate the necessary measurement enhancement for data collection, and related signaling process for distributed and centralized analysis.

6.1.2. ITU

In November 2017, the ITU study group 13 established the focus group on ML for the future network including 5G (FG-ML5G). The objective is to identify the standardization gap for improving the interoperability, reliability, and modularity of 5G oriented ML method. The group aims to generate study reports and specifications on network architecture, protocols, interfaces, algorithms, and data formats for adopting ML in 5G and future networks. It has established three sub-working groups: 1) WG1 is responsible for use cases, services, and requirements; 2) WG2 focuses on data format and ML techniques; 3) WG3 is in charge of ML aware network architecture. After the primary study, the group published technical specifications on architecture for ML in 5G and future networks at the beginning of 2019 [237].

6.1.3. ETSI

To improve the network management experience, ETSI established an industrial specification group (ISG) named as experiential network intelligence (ENI) in February 2017. The aim is to define a cognitive network management framework based on the control model of "observe-orient-decide-act". The essential concept of the ENI is network context awareness and analytics, data-driven policy, and AI-based closed-loop control. It applies various AI techniques to generate context-aware policies for dynamically managing network services according to changing network situations, business models, and user requirements. It is expected to enable the management and control system by learning from its operations and human instructions and realize automatic network monitoring and configuration process. Thus, it can reduce the human effort and errors, operational cost, and time to market of new services. The ISG ENI has released several specifications on use cases, requirements, context-aware policy management, and the framework of proof-of-concept [238].

Besides, another related ISG named as zero-touch network and service management (ZSM) was established in January 2018. The objective is to realize automatic network operation and tasks such as delivery, deployment, configuration, management, and optimization. It focuses on the end-to-end 5G network and service management in the short term and will extend to the future 6G networks later [239].

6.1.4. ISO/IEC

The international standards committee ISO/IEC JTC1/SC42 was established in October 2017. As a joint committee between ISO and IEC, SC42 is responsible for standardization in the area of AI. It facilitates ISO/IEC JTC1 on the standardization program of AI and guides ISO/IEC JTC1 on developing AI applications. Although SC42 has developed several standards on big data and AI including concept and terminology, reference architecture, and the framework of AI system [240], it has not developed any standards on applying AI techniques to mobile networks.

6.1.5. TM Forum

Smart BPM is a Catalyst project founded by TM forum that aims to investigate the potential of introducing AI-based decision modeling in the telecom network business process such as customer management, service provisioning, QoS assurance, and fault management [241]. AI makes it possible for workflow systems to automatically react to exceptional events during network service lifecycle orchestration including planning, delivery, deployment, operation. The DNN is applied in the AI-based support system. By using input data from orchestrator, network management, and network devices, the proof-of-concept model for network fault detection and recovery has been demonstrated.

6.1.6. CCSA

China Communications Standards Association (CCSA) has initiated several studies on applying AI to telecommunication networks since 2017. Specifically, CCSA TC1-WG1 approved the project proposal of a study on the application of AI in telecommunication network evolution. The main study contents include: 1) The application of AI techniques in network management /alarming processing such as fault analysis and root cause identification/ fault prediction. 2) The application of AI techniques in network optimization. 3) The application of AI techniques in the SDN/NFV network for self-management, self-adaption, policy control. In December 2017, CCSA TC5/WG6 launched the project to study the application of AI and big data on wireless communication networks. The major contents include 1) AI and big data-based wireless channel modeling, wireless signal detection, and estimation, network architecture and radio resource management, radio network planning and optimization. 2) The potential impact on existing specifications when introducing AI and big data into wireless communication networks. Meanwhile, CCSA TC5/WG12 initiated the study on intelligent 5G network slicing technology. The main contents include: 1) Typical use cases and requirements on intelligent network slices, management, and orchestration. 2) The requirement of intelligent network slice management and orchestration to the network platform. 3) The potential impact on the existing network system and specification.

Table 6 shows a summary of the major SDO initiatives on the AI-enabled network towards 6G.

6.2. Major industry research and practices

6.2.1. SELFNET

In July 2015, The SELFNET project under the EU H2020 program was founded to create and implement an intelligent network management framework for 5G networks within 36 months. It aims to help 5G network operators to simplify the complicated network management and operation tasks, which decrease operational expenditure, shorten time-to-market of new services, and improve user experience. By leveraging emerging technologies like AI, SDN, NFV, the project aims to provide the capabilities of self-healing against network failures, self-optimization to improve QoE, and self-protection against distributed

Table 6
Related SDO progress on AI enabled network towards 6G.

SDO	Working group	Action description	Time framework
3GPP	SA2	Study enablers for network automation of 5G	Jan.2018 - Dec.2018
		Enhance 5G Arch to support NWDAF	Jan.2019 - Dec.2019
	RAN1/2/3	RAN-centric data collection and utilization	Sept.2018 - Jun. 2019
ITU/ SG13	FG-ML5G/ WG1	Define use case, and requirement of ML in 5G	Nov.2017 - Mar.2019
	FG-ML5G/ WG2	Study data format and ML techniques	Nov.2017 - Mar.2019
	FG-ML5G/ WG3	Define ML aware network architecture	Nov.2017 - Mar.2019
ETSI	ENI	Use case and requirements	May.2017 - Mar.2018
		Context aware policy modeling	Sept.2017 - Mar.2018
		Architecture	Feb.2018 - Mar.2019
	ZSM	Requirements	May.2017 - Oct.2019
		Reference Architecture	May.2017 - Aug.2019
		Terminology	May.2017 - Aug.2019
ISO/IEC	JTC1/SC42	Standardization on AI concept, framework	Oct.2017-
CCSA	TC1/WG1	Study on AI in network elvolution	Dec.2017- Jun.2019
	TC5/WG6	Study on AI in wireless network	Dec.2017- Jun.2019
	TC5/WG12	Study on intelligent 5G core network slicing	Dec.2017- Jun.2019

cyber-attacks. One of the main objectives of SELFNET is network intelligence, which enables the autonomic management of 5G networks by dealing with the detected problems reactively and predicted problems proactively [242]. To this end, a closed-loop control system starting from sensors and terminating at actuators is designed. Although the SELFNET provides a high-level framework of automatic management, appropriated ML algorithms and models need to be carefully designed and verified to solve practical network problems.

6.2.2. CogNet

To cope with the increasing complexity of 5G network management, in July 2015, the EU H2020 project CogNet was launched to reach the vision of automated network management [243]. The project aims to ensure the quality of services, improve operational efficiency, and reduce operational expenditure by developing an autonomic self-managing network management framework. Compared with existing network management architecture, the framework proposed by CogNet is enhanced by both realtime and batch ML techniques to enable an elastic big data ecosystem that can flexibly handle various use cases. The major novelty of the framework is the ML-enabled cognitive smart engine, which makes it possible to dynamically adapt resources to the changing requirements based on real-time learning.

6.2.3. SLICENET

The EU H2020 project SLICENET launched in June 2017 focuses on the cognitive network management and orchestration of the end-to-end slices over SDN/NFV based 5G networks across multiple operator domains [244]. The project aims to develop a new cognitive and integrated 5G network slice management framework for vertical business, establish agile management and assurance of slice services, demonstrate the efficiency of the framework in delivering slice-based 5G services for verticals. The three vertical use cases identified by SliceNet Project include eHealth, Smart Grid, Smart City.

6.2.4. 5G-CLARITY

To facilitate the novel critical communication services for vertical users, the EU H2020 project 5G-CLARITY [245] aims to develop B5G architecture for vertical industry users. The architecture is characterized by a novel access network integrating WiFi, LiFi, and 5G, and novel management components enabled by AI to realize network automation. Besides, it will define novel eMBB and URLLC services with measurable enhancements in terms of low latency, reliability, area capacity, and accurate positioning. An SDN/NFV network management framework embedded with an AI engine will be developed to achieve automate management according to intent policies from administrators. Based on AI-driven management, 5G-CLARITY will enable efficient provisioning, managing, and optimizing network slices.

6.2.5. ARIADNE

The EU H2020 project ARIADNE [246] aims to realize efficient high-bandwidth radio communications by developing critical new technologies for 5G and beyond in an integrated way. First, the project will propose new radio technologies for above 100GHz D-band based wireless communications. Besides, it will exploit opportunities for the advanced connectivity based on metasurfaces by tuning the objects as reflectors for shaping the radio channel environment in D-band. Moreover, to achieve the dynamic management and reconfiguration of metasurface for providing reliable high bandwidth connections, it plans to develop an intelligent management system by employing ML and AI techniques. To realize these concepts, ARIADNE proposes a novel system architecture optimized by a new communication theory framework beyond the Shannon paradigm and develops ML-based approaches for adaptive radio resource management, ultra-reliable connectivity, and E2E network optimization.

6.2.6. MonB5G

Recently, the EU H2020 project MonB5G [247] is established to address the challenges of management and orchestration of massive numbers of network slices with diverse functionality, periods, and performance requirements in the B5G period. To achieve the objective of zero-touch management and orchestration of massive network slices, the project proposes a new autonomic management and orchestration (MANO) framework by leveraging distributed data-driven AI technologies. The hierarchical fault-tolerant and automated data-driven framework incorporates security and energy efficiency as key features. MonB5G will extend the existing MANO and mobile edge computing (MEC) framework with embedded cognitive functionalities and develop trust mechanisms to secure cross-domain operations. Two use cases will be trialed over testbeds to demonstrate zero-touch slice MANO over multiple administrative domains, as well as AI-assisted security situation awareness and policy enforcement.

Table 7 summarizes major industrial projects on the AI-enabled network towards 6G.

7. Open issues and research opportunities

7.1. High-quality dataset from mobile networks

The massive and high-quality dataset is very important for DL algorithms to achieve good performance. As DL models usually contain many parameters, large volume and high-quality data are indispensable to train large and complex models. Without sufficient data, the performance DL approach may suffer from the under-fitting issue. Unlike other research areas such as computer vision and Natural Language Processing (NLP), where sufficient high-quality dataset is available for researchers to verify and compare different algorithms, there is no any public

Table 7
Major industry projects on AI empowered networks towards 6G.

Name	Objective	Key partners	Time plan
SELFNET	Creat and implement an intelligent network management framework for 5G	Eurescom,Nextworks Universidad de murcia Altice,Innorout	July.2015- June.2018
CogNet	Develop an automatic self-manging network management framework to ensure QoS,improve operation efficiency and reduce OPEX	Alcatel-lucent, Telefornica Waterford institute of tech. Technische universitaet Berlin	July.2015- Dec.2017
SLICENET	Develop a new cognitive and integrated network slice management framework	Eurescom,Altice labs EURECOM,IBM, Ericsson Orange,Dell,CIT	June.2017- May.2020
5G-CLARITY	Design B5G architecture based on novel access network and management components by AI to realize network automation	IHP,ACC,I2CAT Ericsson, BOSCH, IDCC Telefonica,UEDIN UGR,UNIVBRIS	Nov.2019- Oct.2022
ARIADNE	Enable high bandwidth wireless communication for B5G based on NR and intelligent management by employing ML and AI	EUROSCOM, Telefonica Nokia,Intracom University Oulu	Nov.2019- Oct.2022
MonB5G	Achieve zero-touch management and Orchestration framework for massive network slice for B5G	CTTC, Aalto, Orange NEC, Ericsson,EBOS EURECOM,Citrix	Nov.2019- Oct.2022

available dataset from mobile networks because mobile network operators keep the collected data confidential due to user privacy concerns. Besides, the data privacy protection regulations from governments limit the open-access of real datasets from communication networks. Therefore, the mobile network industry must generate high-quality datasets from mobile networks after removing or concealing user privacy information. Moreover, dataset collected from sensors and mobile devices is usually subject to loss, imbalance, redundancy, and mislabeling, which can not be used for training directly. Therefore, more research efforts are needed for mobile data collection, aggregation, cleaning, clustering, and anonymization. As potential solutions to mitigate the dataset lacking problem, ML technologies can be leveraged to mitigate the issues. GAN is a promising approach to generating synthetic data for assisting supervised learning tasks. This is especially important for mobile network scenarios where a large amount of real data is lacking. It is worthy to study how to employ GAN to enrich the training dataset by generating synthetic data from limited practical dataset. Moreover, as demonstrated by existing studies [138],[175], transfer learning can significantly reduce the amount of required data to achieve desired performance by reusing the learned model in other similar network scenarios.

7.2. Intelligent network security

AI brings both opportunities and challenges to 6G network security and user privacy protection. On one hand, various ML and DL algorithms have been employed to enhance network security, such as intrusion detection, abnormal traffic detection, malicious user behavior detection. But most of the existing studies are focused on the fixed network side. Only a few works attempted to enhance radio network security by leveraging ML techniques[248].,[249] are good examples of securing future radio networks by DL. Given the open nature of the wireless channel, limited channel capacity, and processing capacity of radio network nodes, the radio network is especially vulnerable to malicious attacks. More research efforts are necessary to enhance the radio security protection. On the other hand, existing ML frameworks and algorithms themselves are facing various security risks [250]. In case security is not considered at the beginning of AI-based mechanisms development, attackers may manipulate the inference that results in wrong decisions [251]. In smart environments of 6G such as autonomous vehicles, intelligent manufacturing, attacks to AI-based control systems may lead to devastating results. Moreover, security risks may happen during operation. Malicious data injection could mislead AI agents to make wrong decisions. For example, a malicious user may broadcast fake signals to mislead the AI training process so that it can access more resources of the shared physical channel while other users are denied. Besides, data poisoning poses another challenge to the unsupervised learning based IDS since it may change the data used for detecting malicious attacks. Moreover, given that large amounts of the real datasets are needed to train AI models, how to efficiently detect the maliciously polluted dataset is another challenge. Therefore, the integrity and privacy of the dataset to train the ML models, the robustness, and confidentiality of the ML models should be well addressed during AI-enabled network mechanisms development.

7.3. Holistic network optimization

Conventionally, approaches like dynamic programming, game theory, and constrained optimization are used to solve various network optimization issues. However, the formulated mathematical model is usually based on the strong assumption on the convexity of objective functions or the ideal data distribution model. As the networks evolving towards 6G become increasingly complex and dynamic, some assumptions will be not realistic. It is more challenging to get the optimum result of the formulated problems by conventional approaches due to large numbers of parameters and constraints. Fortunately, the computational complexity of DL algorithms is controllable and independent from the scale of the network parameters [252]. Although many works have attempted to apply ML/DL techniques to solve various network optimization issues and show encouraging results, most of them focused on a specific network scenario such as UAV, D2D, and Satcom, hardly any work considers the space-aerial-terrestrial-ocean integrated large scale 6G network scenarios. The DRL approaches do not require rigid mathematical models based on any strong assumptions. Moreover, it can address the problem with large sate-action spaces by function approximation, which makes it possible to solve large scale optimization problems that are difficult to be solved by conventional optimization approaches. The recent work [9] on optimizing space-air-ground integrated networks by DL has shown promising results. Further study is needed to realize a close-loop automated 6G optimization system by leveraging DRL. A feedback loop between the optimization policy controller and policy enforcement entities and/or sensing entities makes it possible for the policy controller to iteratively refine system optimization policy/action and reach optimum performance eventually. The remarkable success of Atari and Alfa Go make us believe that DRL will be a key enabler to achieve optimum 6G performance in dynamic and uncertain environments.

7.4. Distributed and real-time intelligence

Most of the existing AI solutions are resource and energy-hungry and time-consuming [42], which may not be practical to handle quickly changing heterogeneous 6G network states and user requirements. Therefore, the mobile AI paradigm comprising both centralized could intelligence and distributed edge intelligence is critical. The distributed and lightweight intelligence embedded at the wireless network edge can significantly contribute to ultra-low-latency services[42]. By analyzing data and making decisions near the place where data is generated, edge intelligence can reduce transmission costs, security risks, and latency during data transmission. However, distributed edge nodes may have different learning capabilities and the local dataset may be different in size and quality. This could potentially lead to instabilities in network control [21]. How to ensure the reliability of edge intelligence relying on local small data is a challenging issue. Sharing partial of data and trained AI models among distributed edge AI agents instead of raw data will significantly reduce the communication overhead and latency. Besides, training high-quality models over time by leveraging incremental learning and adopting trained models via knowledge distillation and transfer learning are helpful to cope with small data availability at the edge. Moreover, to improve the efficiency of existing deep learning techniques, expert-knowledge assisted deep learning is critical. In the context of 6G system, Leveraging data-driven deep learning methods with theoretical models based expert knowledge is of great potential [21]. Although the mathematical models established for 6G system may be inaccurate or intractable, they are helpful for data-driven approaches to optimize or refine the models more quickly. It has been revealed that joint data-driven and model-based approaches can significantly reduce the complexity of purely model-based methods and enable real-time network response. Meanwhile, they can achieve near-optimal performance with much less amount of data compared to purely data-driven methods. More effort is worthwhile to achieve a realistic 6G AI paradigm by combining data-driven deep learning approaches and conventional mathematical models based methods with transfer learning.

7.5. Verification through practical implementation

Most of the existing works on applying ML/DL to mobile network problems demonstrate the performance of their methods through simulations. Only few works [197],[253] attempted to verify the performance through practical implementation. Usually, synthetic network datasets instead of real network data are used in training and validation. Benchmarks used in the literature for validation of ML-based solutions are often far from being realistic due to the big difference between simulation settings and real network environments. For instance, the diverse and dynamic physical channel in practical scenarios is much more complex than the channel environment in the simulation system generated by mathematical models. The actual dataset from real networks is much more diverse than the data traffic generated by simulation software. Although most of the solutions proposed in literature perform well in such settings, the applicability to practical network environment remains questionable. Therefore, there is still a long way to put these ML-based approaches into 6G system. More effort is needed to move forward from simulation-based study to practical implementation based study. To make it possible, open-source and programmable hardware platforms, such as field-programmable gate array, programmable chips, reconfigurable hardware for radio communications are indispensable. Moreover, the authentic dataset from practical mobile communication networks is important for researchers to verify the performance of novel ideas and compare different methods.

8. Conclusion

6G system is envisioned to support various new applications with emerging radio technologies and new paradigms. However, many technical issues remain to be addressed to achieve the ambitious goal of 6G system. AI is expected to play an important role in 6G networks. This article presents the vision of AI-enabled 6G and comprehensively investigates major network issues that can be solved by ML/DL, such as advanced radio interface, intelligent traffic control, management and orchestration, network optimization, and network security. The latest progress of the industry standardization and research projects on introducing AI in the network towards 6G are investigated. By reviewing the latest studies, we identify potential future research opportunities such as high-quality dataset, intelligent network security, holistic network optimization, real-time intelligence, verification through practical implementation. In general, although many academic works have revealed the potential gains of applying ML/DL to mobile networks, the practical application of AI in commercial networks is still quite limited. Therefore, more efforts are needed to make AI widely used in practical networks. Besides, 6G networks are still at the infancy phases, emerging technologies are far from mature. There is a good opportunity to adopt ML in 6G architecture design from the beginning to achieve an AI native 6G. This review will be helpful for readers to understand the latest academia and industry development progress and perform further studies to make 6G more intelligent, efficient, and secure by leveraging AI technologies.

CRediT authorship contribution statement

Shunliang Zhang: Conceptualization, Data curation, Writing - original draft. **Dali Zhu:** Writing - review & editing, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.comnet.2020.107556

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