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A taxonomy of AI techniques for 6G communication networks

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ABSTRACT

With 6G flagship program launched by the University of Oulu, Finland, for full future adaptation of 6G by 2030, many institutes worldwide have started to explore various issues and challenges in 6G communication networks. 6G offers ultra high-reliable and massive ultra-low latency while opening the doors for many applications currently not viable by today's 4G and 5G communication standards. The current 5G technology has security and privacy issues which makes its usage in limited applications. In such an environment, we believe that AI can offer efficient solutions for the aforementioned issues having low communication overhead cost. Keeping focus on all these issues, in this paper, we presented a comprehensive survey on AI-enabled 6G communication technology, which can be used in wide range of future applications. In this article, we explore how AI can be integrated into different applications such as object localization, UAV communication, surveillance, security and privacy preservation etc. Finally, we discussed a use case that shows the adoption of AI techniques in intelligent transport system.

1. Introduction

From the past few decades, Artificial Intelligence (AI) becomes the most powerful technology in solving many challenging problems such as route management, congestion control, topology management, security, and privacy of the communication network. Initially, it was accepted for network monitoring and diagnosis [1], but later, it is being used to optimize the network topology of large scale distributed systems using heuristic algorithms to produce an optimal solution. Non-optimal solutions were otherwise considered impossible to solve due to the combinatorial explosion problem [2]. The aforementioned implementations of AI were considered as its initial usages during the pre-2000 era. But, since its inception, affordable computing was made possible by a large number of Graphics Processing Units (GPUs) and Compute Unified Device Architecture (CUDA) cores diversified the role of AI. Instead of simply designing and optimizing the network topologies, AI can now be used to monitor and secure the network also. Hardcoded algorithms can be used to monitor the network to determine whether any malicious activity in the network occurs. It can also monitor the network load and traffic which helps to prevent the Denial-of-service (DoS) attacks. But, since the network-related algorithms are always predefined, so by applying the AI techniques to such algorithms, we can prevent many attacks on the network. This continuous updates in network algorithms using AI techniques can remove various vulnerabilities in the networks.

The continuous advancements in AI techniques such as machine learning and deep learning techniques make it possible to execute those conventional tasks which were earlier considered as impossible. These advanced techniques gain deep insights into the network and predict various diverse parameters to perform various tasks with high accuracy. They can perform various functionalities such as traffic classification, resource management, and information recognition. They automatically optimize the adaptation of networks by performing network rerouting, congestion control, and Quality of Experience (QoE) optimization [3]. AI has also lead the development of novel networking models such as Intent-based networking, which is an automation process to generate network models according to the requirements of the customers. It allows the teams to raise their needs or intents and feed it to the network, which automatically configures all the devices. Conventionally, it was a long and tedious process where the teams need to submit their network requirements to the skilled network engineers for the configuration of the entire network. Intent-based networking leads to the improved agility, increased operational efficiency, and improved user QoE.

In this direction, one of the most powerful technologies, Software Defined Networking (SDN) provides flexibility and agility required by the enterprises. Its objective is to offer dynamic network control to the service operators where the requirements from the clients are dynamic and ever-changing. SDN decouples the hardware network functions

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Nomenclature

1G	1st Generation
2G	2nd Generation
3G	3rd Generation
4G	4th Generation
5G	5th Generation
6G	6th Generation
ACO	Ant Colony Optimization
AI	Artificial Intelligence
AMC	Automated Modulation Classification
ANN	Artificial neural network
AR	Augmented Reality
ASR	Automatic Speech Recognition
CNN	Convolutional Neural Network
COCO	Common Objects in Context
CSI	Channel State Information
CSS	Cooperative Spectrum Sensing
CUDA	Compute Unified Device Architecture
DBM	Deep Belief Network
DL	Deep Learning
DNA	Deep Network Analyzer
DNN	Deep Neural Networks
DQN	Deep Q-Network
DT	Decision Trees
DVB	Digital Video Broadcasting
EEG	Electroencephalography
eMBB	Enhanced Mobile Broadband
EMR	Electronic Medical Report
GPU	Graphical Processing Units
GRU	Gated Recurrent Unit
GT-CNN	Ground Truth Convolutional Neural Network
HOG	Histogram of the Oriented Gradient
ICR	Integrated Coherent Receiver
IoT	Internet of Things
IRR	Internet of Things Resource Registry
ISOMAP	Isometric Mapping
ITS	Intelligent Transport System
KNN	k-nearest Neighbors
L-SVM	Linear Support Vector Machine
LED	Light Emission Diode
LSTM	Long Short Term Memory
MAC	Medium Access Control
MAP	Maximal Aposteriori Probability
MDP	Markov Decision Process
MEC	Mobile Edge Computing
MIMO	Multiple Input Multiple Output
ML	Machine Learning
mMTC	massive Machine-Type Communications
MRA	Multi-radio Access
MRA	Multi-radio Access
NFV	Network Function Virtualization
NOMA	Non-orthogonal Multiple Access
OFDM	Orthogonal Frequency Division Multiplexing
OLSR	Optimized link state routing protocol
OWC	Optical Wireless Communications
PCA	Principal Component Analysis
PHY	Physical Layer
QOE	Quality of Experience
QOS	Quality Of Service
RAN	Radio Access Network
RBM	Restricted Boltzmann Machine
RF	Radio Frequency
RIP	routing information protocol
RNN	Recurrent Neural Network
SCF	Spectral Correlation Function
SCMA	Sparse Code Multiple Access
SDN	Software Defined Networks
SE	Spectrum Efficiency
SSA	stability based adaptive routing
SVM	Support Vector Machines
TDD	Time Division Duplex
TDD	Time Division Duplex
THz	Terahertz
UAV	Unmanned Aerial Vehicles
URLLC	Ultra-Reliable Low-Latency Communications
VLC	Visible Light Communication
VR	Virtual Reality
YOLO	You Only Look Once

(keep it at the control plane) from the data plane or forwarding plane to make the network management easy and flexible. AI techniques can be incorporated in the SDN controller to automate the task such as load balancing, flow routing, and network security using algorithms such as Ant Colony Optimization (ACO), decision tree, and Artificial Neural Networks (ANN) [4–6]. According to the latest report [7], around 53 percent of the service providers are expected to incorporate AI in their networks.

In recent years, the potential applications of AI integration with networking has been on the rise. SeDaTiVe framework was proposed by Jindal et al. [8] which applied deep learning to SDN's for smart vehicles to control the network traffic. Another approach was proposed to reduce the costs of data aggregations from IoT devices, using a fog based framework called FESDA which was able to reduce the costs by 50% [9]. Another, data aggregation framework for the healthcare domain used fuzzy-based classifiers to ensure systematic decision making from the collected data which had improved efficiency over the traditional cloud computing-based platforms [10]. There are various other technologies, apart from AI that have contributed to the field of communication [11]. Due to Blockchain technology, there is a great increase in the performance of the communication applications like Internet of Vehicles (IoV), SDN-enabled vehicle-to-grid environment, etc. [12,13].

Although 5G networks are sufficient for the current applications, however, it has some limitations and cannot support future applications. For example, Hologram communications may require data rate in TBps, while 5G supports a maximum rate of *10* Gbps. Also, the integration of IoT is increasing day-by-day and has led to a huge spike in the number of devices that need to communicate with each other and to the host. So, 5G may not be able to provide network connectivity to such a large number of devices/users in the future, resulting in network congestion. The current methodology of configuring and optimizing the networks is done manually, which cannot be scaled to the ultra-large-scale wireless networks, which are dynamic and complicated. These limitations are expected to be overcome by the upcoming 6G networks which provide several functionalities integrating with AI techniques as shown in Fig. 1.

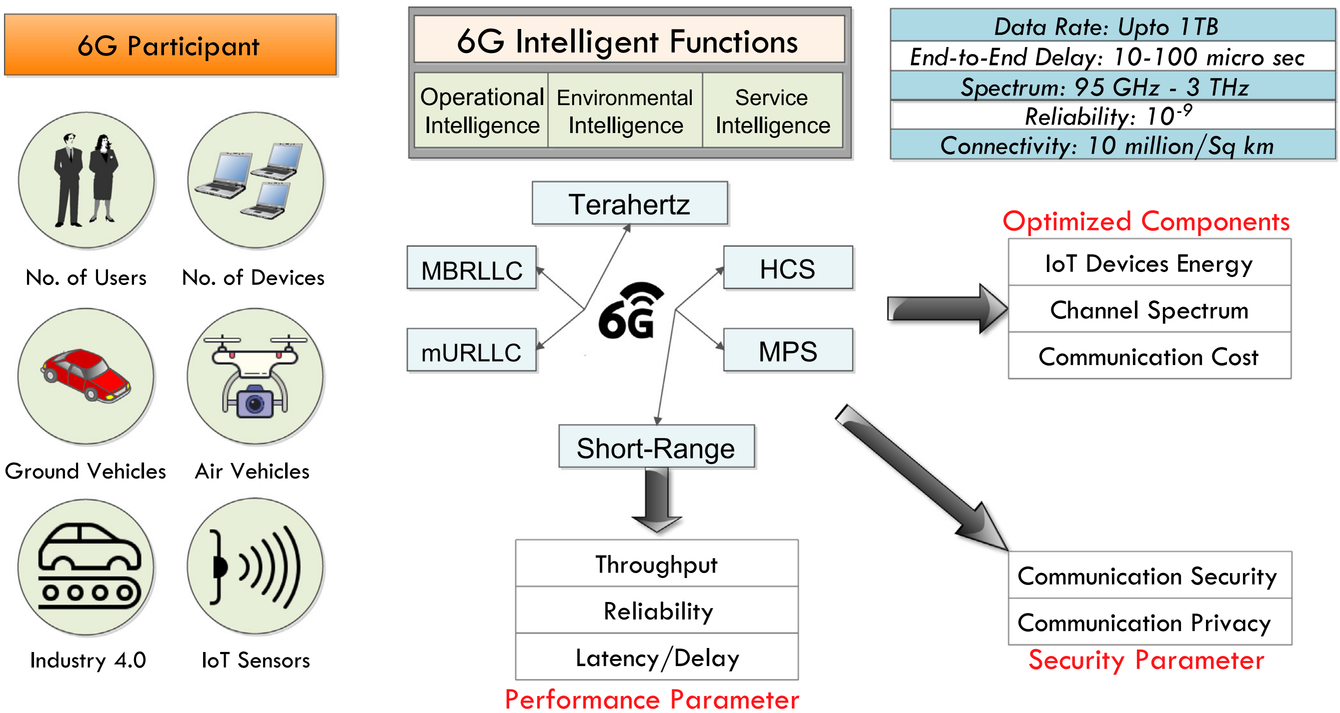

Fig. 1. 6G basic concepts and its services.

1.1. Contribution of this survey

With respect to the aforementioned discussion, it has been observed that 6G communication is the most powerful and emerging technology of the modern era. The integration of AI with 6G revolutionize the communication aspects in terms of routing and decision making. Based on the above, the following are the major contributions of this paper.

- We discussed 6G concepts and services and presented a taxonomy based on AI-enabled 6G applications.
- We proposed the AI integrated 6G architecture by highlighting various application scenarios.
- We highlighted several future challenges and implementation issues in 6G communication networks.
- At last, we described a use case of Intelligent Transportation System (ITS) and then proposes its architecture integrated with the above-proposed architecture of AI-enabled 6G.

1.2. Scope of the survey

While the 5G network has just started to roll out commercially, yet its impacts on the economy, and society are still unknown. Many researchers across the globe have started exploring 6G communication networks and give their theories and architectures. Most of the papers focused on what 6G technology is and why it is necessary for the future. Authors explored that what are the new features in 6G and analyzed services and applications where it can play a vital role. But, there exists no in-depth survey which explores all 6G concepts, services, AI integration, architecture, a taxonomy for AI techniques in 6G networks, real-life use case, and future scenarios. So, in this paper, we address all the aforementioned concepts and architecture in detail.

There is some literature [14,15], and [16], most of which explained the concepts of 6G but not focused on how AI can be integrated to make 6G network more robust and resilient. Some proposals such as [17–19], and [20] explained how 6G with combination of AI helps in reducing the delay and increases the reliability of future data-intensive applications. However, they explained theoretically but not proposed any architecture to analyze the application implementation. Zong et al. [21] explained the evolution of wireless generations and then explained 6G with architecture, but applications, where 6G can play a vital role, were not discussed. In Table 1, we presented a summary of various surveys related to 6G and their differences with the proposed survey.

1.3. Organization and reading map

The rest of the paper is organized as follows. Section 2 presented the background of communication networks starting from 1G to 6G and discussed its application scenarios. Then various AI techniques are explained which can act on various 6G communication layers. Section 3 discusses the review methodology used to conduct this survey. In Section 4, we discussed the traditional 6G architecture and proposed a new AI-enabled 6G architecture. Section 5 highlights various AI techniques that can be implemented in 6G. In Section 6, we discussed various shortcomings of 6G, and then in Section 7, we presented a use case of an intelligent transportation system. Finally, Section 8 concludes the paper.

2. Background

This section discusses about the background knowledge of various concepts used in the proposed survey such as

2.1. Communication evaluation

With an increased communication requirement of end-users and network operators, the QoS, QoE, and to achieve more reliable wireless communication network which is the main reason behind evolution in the communication channel from first-generation (1G) to fifth-generation (5G) and is now switching towards the sixth-generation (6G) networks as shown in Fig. 2. In the 1980s, the first analogous communication system was introduced with limited connectivity and only restricted to voice transmission. the different wireless generations were introduced with the new aspects of services, regulations, and innovations [26]. The 1G communication network was introduced in the late 1980s, which was used to transmit analog signals, i.e., voice only. This network architecture provided maximum data rate up to

Table 1
Comparison of our proposed survey with the existing surveys.

Authors	Year	Objective	Merits	Demerits	1	2	3	4
Yastrebova et al. [15]	2018	To present future challenges and application which can be resolved by 6G network	They showed how future network architecture for 6G should be	Role of AI in 6G is not mentioned	Y	N	N	N
Huang et al. [14]	2019	To provide detailed survey on Green 6G	Explained how 6G can be better than previous generation networks	AI integrated approaches to develop 6G were not discussed	Y	N	N	N
Strinati et al. [16]	2019	To provide an introduction of 6G networks	Discussed various limitations of 5G and importance of 6G in detail.	Detailed survey of AI approaches in 6G were not discussed	Y	N	N	N
Zhao et al. [22]	2019	To present a survey on Intelligent reflecting surfaces for 6G	Surveyed recent reviews and identified future challenges in IRS field for 6G	Lack of proper 6G architecture based on IRS and involvement of AI in their work	Y	Y	N	N
Zhang et al. [17]	2019	To explain key technologies for 6G and explore potential application of 6G networks	Explained how mobile ultra broadband, super IoT and AI could help 6G networks to achieve its goal	Architecture and hardware design not discussed	Y	Y	N	N
Tang et al. [19]	2019	To show how 6G can revolutionize vehicular network	They discussed how Machine learning can help to make vehicular network better in 6G architecture	Does not focus on 6G technologies and its application in diversified field	Y	Y	N	Y
Saad et al. [23]	2019	To encourage more ingenious research ideas around 6G	Focused on future applications for 6g and their enabling technology	6G architecture, working and structure not emphasized	Y	Y	N	Y
Loven et al. [18]	2019	Presented a new model for 5G which will then be applied to 6G	Discussed the merits and the demerits of AI at edge computing	Discussed architecture based on edge computing only and did not discuss 6G architecture not its workings	Y	Y	N	N
Zong et al. [21]	2019	To present new system architecture for 6G	Discussed limitations of 5G and presented new use-cases for 6G	Architecture based only upon photonics and AI are discussed	Y	Y	Y	N
Yang et al. [24]	2019	To present the AI enabled intelligent 6G architecture and its applications	Discussed AI enabled 6G architecture and its usefulness in 6G applications in detail	Taxonomy is not presented and role of AI in ITS and Dynamic Spectrum Allocation not presented	Y	Y	Y	N
Giordani et al. [25]	2020	To explain technologies that will bring change in future generation 6G networks	It discussed various applications where 6G can a play a vital role	AI approaches to make 6G network more robust not discussed	Y	N	Y	N
Murshed et al. [20]	2020	To survey various machine learning techniques applied in Mobile Edge Computing	Explained ML techniques used in Edge Computing applications and future challenges in detail	Only one application of 6G networks based on ML was discussed i.e. Mobile Edge Computing	Y	Y	N	Y
The proposed survey	2020	To provide detailed survey of AI techniques used for 6G networks	Discussed AI integrated 6G architecture and surveyed various AI techniques used for various applications of 6G	–	Y	Y	Y	Y

1 - 6G focused, 2 - AI focused, 3 - AI proposed 6G Architecture, 4 - Taxonomy available.

2.4 Kbps [14]. The major drawback for the first generation of wireless communication was low transmission efficiency, lack of security and privacy, and problematic hand-off mechanism.

Later, 2G was introduced to improve the transmission and spectral efficiency, which was entirely based on a digital modulation approach such as Code Division Multiple Access (CDMA) and Time Division Multiple Access (TDMA). Global System for Mobile Communication (GSM), General Packet Radio Services (GPRS), and Enhanced Data rates for GSM Evolution (EDGE) standards were developed for 2G digital cellular networks. It achieved the data rate up to *384 (downlink) and 60 (uplink)* Kbps and also supported services like Short Message Service (SMS), Multimedia Messaging Service (MMS), voice, and peer-to-peer networking (P2P) [14,26]. Powerful digital signals were required for mobile phones to work, and also 2G had difficulty in processing video steamings. Due to these reasons, the next-generation 3G has evolved with high data transmission rate of maximum *64 (downlink) and 25 (uplink)* Mbps [27]. It supported various advanced services, which include high-speed Internet access, web browsing, GPS navigation, and UHD video access [14]. 3rd Generation Partnership Project (3GPP) was established to develop the protocols for mobile telecommunication system which further lead to achieving global roaming [28].

The existing network technologies further evolved with the introduction of an Internet Protocol (IP) based 4th generation network [30]. This technology provided an high-quality of services and security that

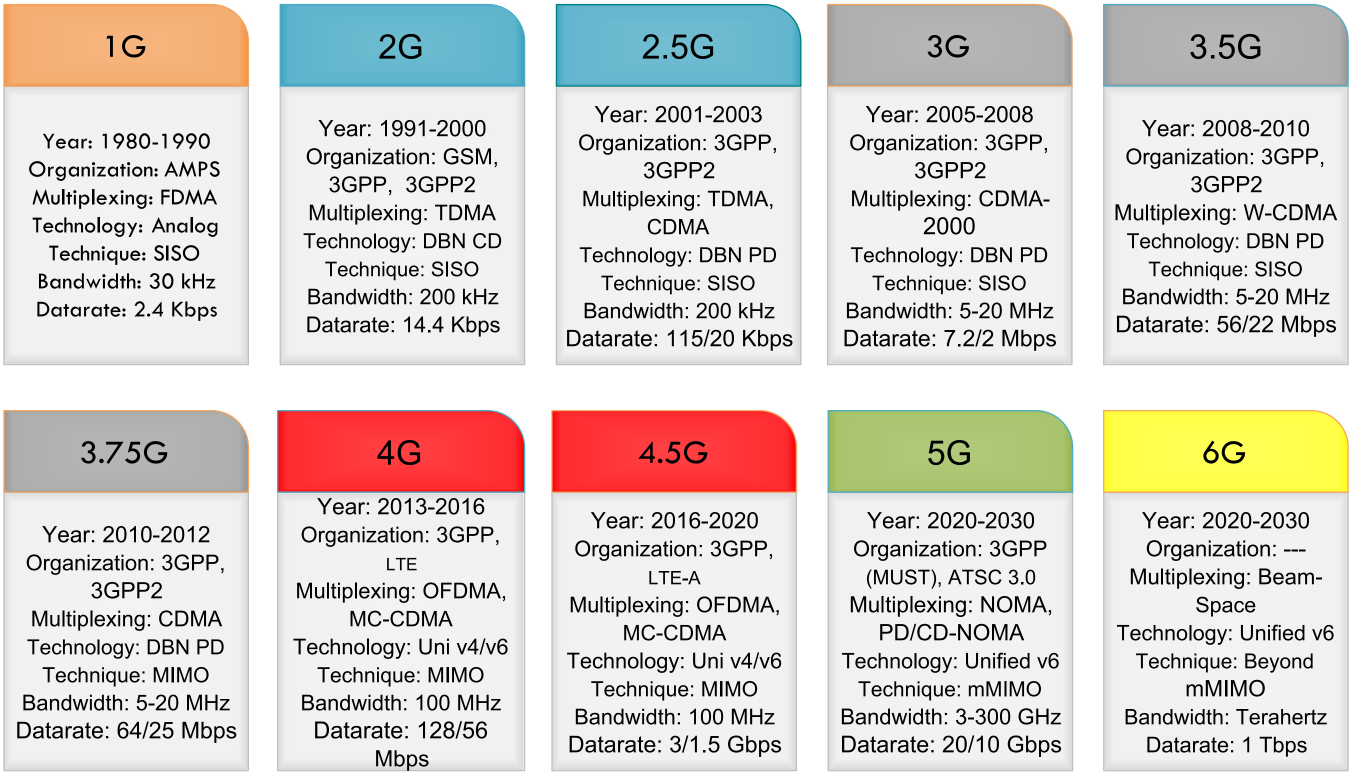

Fig. 2. Timeline of communication networks [29].

can provide high speed from *100* Mbps to up to *1* Gbps. *4G* has solved the drawbacks of previous networks by reducing latency and increasing the network reliability and data transmission rate. It further provided services like Digital Video Broadcasting (DVB), High Definition TV content, virtual navigation, and video chat. The key technologies that *4G* facilitates include Multiple Input Multiple Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM) [31].

To satisfy the diversified requirements and to amplify service provisioning. It is important to transform the current cellular networks to 5th generation networks with cutting-edge technologies [30]. Since the introduction of 5G in networking technology, it was believed to be a key enabler by providing noteworthy services consisting mainly of three frameworks- (i) massive Machine-Type Communications (mMTC) which can support a large number of connected devices, i.e., up to *10 lakh* devices per km^2, (ii) Enhanced Mobile Broadband (eMBB) that operates at spectrum bands of large bandwidth above 6 GHz to provide high data rates up to 1 Gbps [32] for smartphone users and (iii) Ultra-Reliable Low-Latency Communications (URLLC) that focuses on real-time critical-application such as telesurgery, industrial automation, and vehicular network providing reliability of *99.999%* and latency in the order of milliseconds, i.e., <1 ms [17,33]. Rather, 5G mainly worked by welcoming the intelligence to moderately enhance both Spectrum Efficiency (SE) and Energy-Efficiency (EE). Though this network had provided mechanisms for different existing services and have enabled the full integration of complete intelligence, it is still a demanding work for network operators to resolve complex configuration issues and to fulfill the service requirements [30,34].

Still, before the implementation of 5G network, a new discussion has already started about what services and applications of a new generation of mobile systems should provide.

2.2. 6G concepts and services

After the four decades of networking and development of five generations of communication networks, the availability of wireless portable devices has increased exponentially. Now, this is the era where vehicular connectivity and the Internet of Things (IoT) are growing at an exponential rate. This has motivated the network provider to fulfill the ever-growing demands of the connected world by introducing the next wave of communication networks called 6G networks by the year 2030. However, the 5G network is operating at high frequency in *mm Wave* band [35]. 6G could become more advance by using spectrum technologies through *terahertz (THz)* and optical communication [25].

The electromagnetic spectrum for the *THz* band is least studied due to the lack of *THz* transceivers. The problem with *THz* frequency generation is that its value is quite low for photonics-based devices, which are used to generate optical signals and are extremely high for electronics-based devices used to generate microwave signals. But with the emergence of new graphene-based technology, the generation of *THz* frequency signal seems to be possible due to the electrical and optical properties of graphene. One problem with the signal is that it suffers from spreading loss due to the expansion of electromagnetic waves. This loss increases quadratically with operating frequency and the distance between two communication nodes. In *THz* signals, molecular absorption loss is also caused due to conversion of partial energy of *THz* signal to the internal kinetic energy of molecules in air [36]. If we take L_s as spreading loss and denote L_a as molecular absorption then free-space path loss is calculated as Lp = $L_s L_a$.

As pe the interpretation form the paper [37], it can be clearly seen that *THz* band support only short-distance wireless communication as the path loss exceeds *80* dB even when distance is as small as *1* m [37]. To overcome this limitation, various techniques such as ultra-massive MIMO communication, distance-aware physical layer design, reflectarrays, and intelligent surfaces were introduced [38].

Optical Wireless Communications (OWC) has been introduced as a supportive technology for RF-based mobile communications, which includes different frequency bands such as infrared, visible light, and ultraviolet spectrum [25]. It is commonly referred to as Visible Light Communication (VLC) technology. The visible light spectrum band has the maximum efficiency and is also the most favorable spectrum of

OWC due to its adoption of Light Emission Diode (LED). The most important and useful characteristic of LED is its ability to quickly change its light output intensity, which allows the data to be encoded in the output light in various ways, VLC has taken complete benefit of it to attain the two-fold purpose of lightening and high-speed data communication [39]. The responsibility of VLC is to complement RF communication with the help of piggybacking.

VLC is more developed as compared to *THz* communication because of cost-effective experimental platforms. For shorter ranges of less than a few meters, VLC is preferred over the classical radio communication networks [40]. The advantages of VLC are listed as follows:

- Provides an ultra-high bandwidth in the order of *THz* and the other advantage is that the spectrum is unlicensed and free.
- Consumes low-cost illumination sources as base centers, which hardly require construction and maintenance costs, which was mandatory for classical RF communication.
- The major advantage of VLC is that it uses visible light that cannot pass through opaque objects, which means the data in the network is confined to one closed room and guarantees the transmission privacy and security, and reduces the significant inter-cell interference.
- Finally, as VLC does not produce electromagnetic radiation of its own and is shielded against external electromagnetic interference as well, which makes it appropriate for extraordinary conditions sensitive to electromagnetic radiation like aircraft and hospitals [41].

Due to its working, data rates in VLC rely heavily on lighting technology [42]. Micro-LED is the best LED Technology, having a data rate of at least 10 Gbps. It is expected that VLC data rate can reach to even *Tbps* in the future [43]. There are few advanced utilities that cannot be realized with the current communication network technology but are expected to be implemented for the next-generation 6G networks as follows.

- *Holographic Communication*: Services and Communication in 5D consisting of all human senses information (Touch, Smell, Sight, Taste, Hearing) are predicted to rise with new holographic communication (HC). The applications with holographic communication are expected to provide high-precision, deterministic and best-guaranteed services with 6G communication [15]. In HC, we can watch cricket matches not only as video on TV but as a holographic model, which enables the viewing angle of our choice. It demands extremely high data rates, i.e., in terabits per second [16].
- *High-Precision Manufacturing*: The main aim of manufacturing industries is to automate the tasks with high-precision communication and automation technologies compared to the humans generally do [16]. 6G offers extremely high reliability and massive ultra-low latency to the manufacturing tasks. Real-time information transmission is needed in industrial networks, which converts into an extremely low delay jitters [44].
- *Sustainable Development and Smart Environments*: With the importance of data security, the technologies such as IoT, cloud computing, fog computing, and wireless communication plays a vital role in improving the quality of life and achieving the global sustainability. 6G network envisions 3D communications, which significantly contribute to the development of smart cities, improve healthcare services, and smart transportation. For example, in autonomous driving vehicles, the communication parameters such as reliability (above *99.999%*) and latency (below *1* ms) are essential to prevent accidents and help to take dynamic decisions efficiently [16]. High data rates in terahertz are essential to provide intercommunication between the cars that can help to reduce accidental risk. On the whole, this can be achieved with a 6G communication network.
- *Enhanced Energy Efficiency*: It is the most important service provided by the 6G network. Energy consumption plays a vital role in sustainable development. 6G also have productive communication strategies for enhancing energy efficiency [45]. The vision is to accomplish without battery communication wherever conceivable, focusing on communication efficiency on the request of 1 pJ/b [46].

2.3. AI techniques

AI is a branch of computer science that empowers machines to think and act like humans. It incorporates techniques like machine learning, deep learning, optimization theory, game theory, and evolutionary algorithms. When it comes to machine learning, it is based on the principle that machine can learn by identifying patterns from the given data (training data) and then make decisions accordingly with minimal human intervention [47,48]. Machine learning techniques like supervised learning, unsupervised learning, and reinforcement learning are being used in solving current problems and increase its efficiency in communication systems through 6G networks.

2.3.1. Supervised learning

In supervised learning, the machine learns from training data where each input is mapped with a fixed target. It required a predefined data set to learn and increase the performance of the system. It is broadly categorized into regression and classification algorithms. The regression algorithm predicts the real or continuous values based on available input features, whereas the classification algorithm categorically labels each input data, which mainly includes Support Vector Machines (SVM), logistic regression, k-nearest neighbors (KNN) and Decision Trees (DT) [49].

2.3.2. Unsupervised learning

In unsupervised learning, the training data is unlabeled, which means the values that are not assigned to a class [47]. In this type of learning, no prior information of the desired system is available. For instance, the input noisy data symbols can be utilized to train the model by clustering the points for generating the nonlinear decision boundaries for mapping of the symbols according to the constellation maps [50]. This method is typically used to classify the systems by detecting useful clusters in the input data [49,51,52]. The learning methods used for unsupervised learning are *k*-Means Clustering, Principal Component Analysis (PCA), and maximum likelihood learning [29]. It has the potential to perform a large range of operational tasks associated with features extraction, features classification, distribution estimation, and distribution-specific samples generation.

2.3.3. Reinforcement learning

It works on the goal to maximize the reward, i.e., it converges to the best possible path by making the best-suited decisions on what actions to take through interacting with the surrounding environment [53,54]. In other words, it takes feedback from the system and produces better results. A model-free distributed reinforcement learning method for power allocation is proposed [55], in which Channel State Information (CSI) and QoS indicators are exploited to transmit power [56]. Classic reinforcement learning algorithms include Q-learning, Markov Decision Process (MDP), actor–critic (AC), policy learning, and value-based reinforcement learning.

2.4. Integration of AI for 6G networks

The advancements that 6G networks bring in the field of networking and communication will revolutionize the field by making it multi-layered, highly unpredictable, heterogeneous, and available at large scale. The challenges that 6G networks have to face are seamless connectivity, 100% uptime, and assured Quality of Service (QoS) requirements of the large number of devices which also include the always increasing IoT devices [57], and the large amount of data produced from such devices which need to be processed and analyzed.

All these challenges and issues in the growth of the 6G networks can be solved with the integration of AI with 6G networks. AI has extremely high learning, analysis, classifying, and recognizing ability that will aid 6G networks to implement performance optimization, knowledge discovery, sophisticated learning, structure organization, and complicated decision making. Adding AI with 6G has many benefits and some of them are mentioned below.

2.4.1. Role of AI in sensing

The IoT devices are projected to above 125 billion by the year 2030. Interconnecting everything ranging from traffic lights, satellites, and home appliances such as televisions, refrigerators, air conditioners, and door locks generates an ample amount of data that the current network infrastructure is not able to cope with it. AI techniques can be used in such situations. It can classify the data as trivial or as important and send only the important information. AI can also detect anomalies such as intruders in case of a security system and send that information over the network.

6G offers high-reliability and low-latency and meanwhile, sensors need to be accurate in a real-time environment. It is difficult to manage since 6G networks are dynamic in nature. Several techniques can be incorporated as

- *Local Intelligence*: Currently, raw data is collected from a group of sensors and transferred over a network to a high-computational device where the processing of data is performed. This puts an enormous load on the network and also increases its power consumption. Thus, a system is designed whose goal is to minimize the amount of data send over the network without any loss of important data and also saves the power consumption. This can be done with pre-processing at the sensor site with the help of an Artificial Neural Network (ANN). However, for the maximum benefit, the appropriate architecture, as well as the network topology, must be selected.
- *Deep Corporate Sensing (DCS)*: Spectrum sensing can be used to protect the primary user from an interference. The primary user has the main task of relaying all the information collected from various secondary users to the next layer. Cooperative Spectrum Sensing (CSS) can be used for this with more power consumption. It is due to the sensing of a spectrum and reports the findings to the centralized location. CSS uses a mathematical model to combine the results of secondary users, whereas, in DCS, a Convolutional Neural Network (CNN) can be used for the same [58].
- *Data Fusion from Multiple Heterogeneous Sources*: Number of different sources of data leads to data heterogeneity with data coming in various different forms (text, numbers, and floating-point numbers) each with a different mode of representation. Fusing all the data from different sources and getting meaningful information might be a difficult task. Bayesian learning and advance neural networks such as RBM, DBM, and CNN can be used to perform the fusion [59,60].

2.4.2. Role of AI in data mining and analytics layer

This layer is tasked with summarizing the massive amount of data collected by the various devices and sensors. PCA and Isometric Mapping (ISOMAP) algorithms can be used to reduce the dimensionality of the data and convert it to a more compact dataset as a task of this layer. It reduces the computational time by a substantial amount. The said algorithms can also filter out the interference and the abnormal data values from the raw data. Analytics is used to extract valuable and important information from the raw data [61]. It discovers new patterns in the data, which then can be used to select the most suitable model for a given task. It can also help to select the suitable protocol, network architecture, resource allocation, routing protocol, and discover the constant noise in signals.

2.4.3. Role of AI in control network layer

The AI-enabled control network layer in 6G means a layer which consists of learning, optimization, and decision-making properties. By gathering appropriate information and data from the preceding layers. The control layer enables devices to learn, choose convenient power control, routing management, and other vital actions to give assistance to diversified services for the network communication systems [62]. The biggest advantage of integrating AI with these functions in 6G networks is that each agent would get issued with an intelligent learning model to spontaneously gain knowledge to make decisions on their own. By integrating AI with the control network layer, now 6G has the ability to occupy end-to-end design of the network, resource management, network slicing, and other characteristics by discovering different requirements of the application. This characteristic has combined 6G and AI to achieve self-configuration, self-organization, self-healing, and self-optimization [62].

There are various examples where AI assist 6G networks to work efficiently with the least possible issues and challenges. Supervised deep learning-based Recurrent Neural Network (RNN) approach has shown the capability to capture the irregularity in RF components. Here, RNN learns the irregularities in the power amplifier arrays and tries to optimize the minimal transmitted power level at transmitters [63]. By this, the task of achieving the optimal energy-efficient variables and RF irregularities have been interpreted [64]. Conventional optimization algorithms might not be applicable for 6G networks because of the complexity in 6G networks, due to this optimization task of QoS, Q0E, and connectivity is a challenge for these networks. But, when AI was introduced, network parameters and architectures can be easily optimized as AI provided auto-learning models for network optimization by permitting operators for optimizing necessary parameters to adopt better services for its components and devices.

Another deep learning-based approach has introduced Software-defined networking (SDN) and Network Function Virtualization (NFV) into the model of 6G networks for better enhancement, which has the capability of quickly optimize network parameters to achieve intelligent specifications like virtualization and softwarization [65]. For 6G networks, decision making is also an important and challenging task that makes the agents to make decisions wisely. The main objective of decision making in 6G networking is to select the global actions having the greatest benefits and optimal variables in *mm Wave* of *THz* transmission systems based on existing information they have, and also adopting the tolerable and adaptable spectrum handling system for large multi-access scenarios. All these issues and tasks can be easily and efficiently achieved by applying machine learning and deep learning approaches like game theory, optimization theory, and reinforcement learning [62].

2.4.4. Role of AI in application layer

The aim of this layer is to improve the service performance rate of smart applications. 6G network with benefits of AI helps in the development of various mission-critical applications such as smart healthcare, automated industries, smart city, and ITS. Machine learning plays an important role in wireless network optimization, which enables intelligent resource management mechanisms in a real-time environment [66]. This allows the system to make intelligent and dynamic decisions that improve system performance continuously. AI in the 6G network is necessary for services like autonomous driving, industrial control, and drone guidance, which require real-time and low latency operations [67]. Intelligent resource management can be improved by taking cost dimension metrics in terms of resource efficiency into account. Here, resource efficiency is calculated by taking energy, computational, storage, and spectrum utilization efficiencies into consideration.

Table 2
Research questions.

Q.No	Question	Objective
1	What is 6G and why is it needed?	Detailed Architecture of 6G explained along with its potential benefits.
2	What is the role of AI in networking?	Different AI techniques are explained along with their use and advantage in each layer of communication.
3	Discuss the solution taxonomy and comparative analysis of AI techniques in 6G.	The solution taxonomy and comparative analysis based on existing surveys on AI Techniques in 6G is explored.
4	What the different application areas in 6G in which AI can be incorporated?	It is expected that the survey will explore the various applications of 6G and its shortcomings and possible AI solutions for each.
5	Discuss various challenges in different areas of 6G communication.	It aims to provide information on open issues and research challenges in various areas of 6G communication.
6	How this study is applicable in a real-life scenarios?	It aims to provide information on the usefulness of incorporating AI techniques in 6G networks.

Table 3
Quality evaluation.

Q.No.	Question	Answer
1	Does the given paper have any reference to AI techniques or 6G networks?	YES
2	The papers gave an overview of AI techniques for 6G where the words “AI methods” are not being used for 6G, are such papers excluded?	NO
3	Do the abstract, title and the content of the given paper describe “AI techniques for 6G”?	YES
4	Do the abstract, title, and content of the given paper describe AI techniques for 6G or its other sub-areas?	NO

3. Review methods

This section presents the methodology considered to conduct this survey.

3.1. Review plan

The proposed survey begins with identifying research questions (RQ), related data sources, database search criteria, inclusion and exclusion criteria, and quality evaluation. We first identified relevant material for our survey, then the material is checked for quality, and then only the information pertaining to the purposed survey is taken and cited.

3.2. Research questions

The proposed survey identified the research questions from the existing literature on AI Techniques for 6G networks, as mentioned in Table 2.

3.3. Data sources

A broad overview of all topics was necessary for this comprehensive survey. We only used standard peer-reviewed journal databases (for example, ACM Digital Library, MDPI, Springer, IEEEXplore, Science Direct, Elsevier) to search the existing literature and the electronic data sources recommended in [68,69]. Other resources we utilized as technical books pertaining to the topic, white papers, patents, predicting websites and also online blogs related to the existing surveys.

3.4. Search criteria

In this criteria, search using keywords like “AI techniques for 6G”, (“6G Architecture” AND “6G enabled networks”) and others. It was a case for several research papers in which we had to do a manual search since the search string was not present either in the title or its abstract.

3.5. Criteria of inclusion and exclusion

AI can be used in a variety of application areas, so the search string “AI techniques in 6G” often gave irreverent to our survey. To ensure we had an ample number of papers at hand, we also included papers from 2020 early access. To broaden our research field, we also included data from other resources such as white papers and surveys conducted by renowned companies, survey articles, technical papers, and patents.

3.6. Quality evaluation

In this section, to ensure quality, evaluation has been conducted on the papers working on the recommendations by the Database of abstracts of reviews of effects (DARE) and Center for reviews and dissemination (CDR) [68]. Mostly, quality and reputed publications were considered to filter and select the research papers to perform a systematic review of AI techniques for 6G communication. The various quality hiding questions given in Table 3.

4. 6G architecture and its components

The massive growth in the usage of smart devices leads to more number of connected devices and tremendous growth in IoT based applications leads to enormous amount data generation, which leads to an exponential increase in data traffic [70]. Due to this, the current solutions may give low latency and reliability and are not suitable for holographic communication, high-precision manufacturing, remote surgery, enhanced energy efficiency, and instant data transmission. A new future generation 6G technology is required [71] to implement the aforementioned applications smoothly. This would ensure the bolster up of both existing and new applications. In order to understand all applications and services of future networks, and to satisfy the above-mentioned requirements, we have proposed the potential communication architecture for the future.

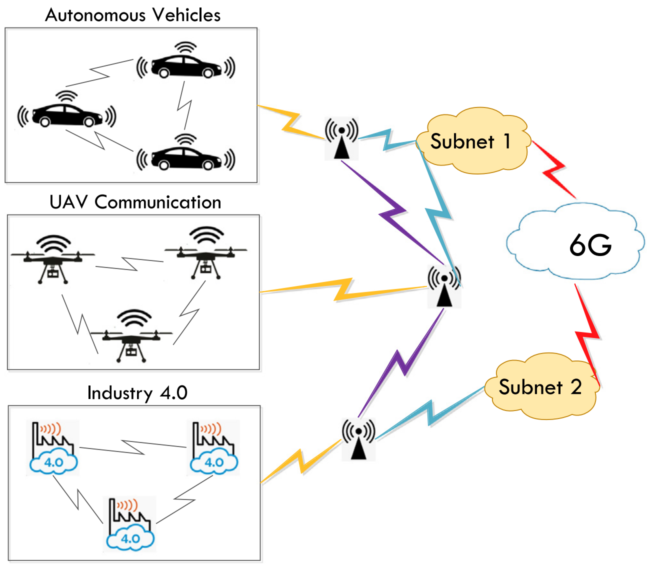

Fig. 3. 6G architecture with sub-networks for different application services [72].

4.1. Traditional 6G architecture

4.1.1. Sub-network architecture

Communication architectures till 4G were mainly focused on providing voice and data to the end-users over the Internet, whereas the 5G system brings an evolved architecture to fulfill the challenging industrial environment requirement by supporting time-sensitive networking (TSN) bridge functionality [73]. Using the path of 5G network, 6G network designers work to replace wired connectivity by providing reliability in various connectivity scenarios ranging from static, isolated devices, to the mobile group of robots and drones [74] which are required to communicate with each other and also should be able to communicate directly to the main network as shown in Fig. 3. To achieve the low latency, high time and spatial domain reliability, and high data rates it is required that each 6G sub-networks ensure critical services without any interruptions even in the case when there is poor or no connectivity to the wider network. Hence, it is necessary that each sub-network collects and analyze its local data and upgrade locally as well as dynamically [75]. The execution of 6G services can be dynamically split between the devices, which are part of a sub-network. One of the main advantages of sub-network based 6G architecture is the security and resilience to the lowest level of devices in the sub-network. Thus, this architecture will ensure native TSN over wider areas with security [72].

4.1.2. Converged RAN cores

Another important component in 6G architecture is Radio Access Network (RAN) convergence. In previous networks, especially in 5G, the base station was divided into two major units: Centralized Unit (CU) and Distributed Unit (DU). The CU consists of non-real-time layer 2 and layer 3 functions, while DU consists of lower layers of user and control plane protocol stack having physical layer 1 and real-time layer 2 [72]. The CU is always executed as a virtualized application in the edge cloud. The core functions used in 5G, turn out to be progressively decentralized as the sum traffic through the core increments significantly. With the increase in centralization of the higher-layer RAN core functions and the circulation of the core functions, simplifications can be achieved by joining some of the RAN and core functions into single entities. Thus in the 6G era, it is important and expected to merge both 5G RAN and core functionalities to reduce to set of functional blocks, which would result in core-less RAN, which is more precise in user plane [72].

4.1.3. All-photonic RANs

The classes of 6G communication networks, namely ultrahigh-speed with low latency communications (uHSLLC), ubiquitous mobile ultra-broadband (uMUB), and ultrahigh data density (uHDD) need ultra-broadband, and ultra-low latency simultaneously, which cannot be possible with the help of 5G Networks. Recent and on-going research in this field have investigated that these ultra-fast signal processing, dependent on devices which are optically integrated that might create an evolution in future RANs.

This type of RAN relies on two important components, 1st is the photonic engine which comes up with extremely high broadband signal generation and processing, and 2nd is the All-Photonic AAU dependent on a photo-diode coupled antenna array. The optical signals which are found at the downlink of these AAUs are transferred to the integrated, coherent receivers (ICRs) for detection and processing. The UTC-PD has a powerful yield and its arrays are able to convert the optical signals into electrical signals that are straightforwardly used to carry away the RAN components. The array antenna elements are used to send RF signals to graphene-based electro-absorption modulators (GP-EAMs), which are used to strongly convert the RF signals to the useful optical signals by using optical in-phase modulation. The useful optical signals are then multiplexed and sent to the optical engines [76]. After all, these components are combined to build an All-Photonic RANs. The RF signals and optical arrays are then split into large and appropriate bandwidth using the modulators and ICR arrays, which outputs into a full spectrum RANs.

One of the most interesting characteristics of AAU is that, if its arrays consist of components made up of RF and optical antennas, then it can be utilized as an RF and optical wireless system simultaneously. All-Photonic RANs can execute an entire spectral assembled framework for detecting, imaging, and communication by bridging RF to the optics. It has radar/lidar, which has the capacity to deal with many sensing tasks and services that might help 6G in the field of transportation systems, ITS. The convergence found in sensing and communication is more likely to produce multiple functions and suggest that 6G Networks will become the multitasking and multipurpose system to provide various services that are necessary for AR, VR, and RF mapping of the radio environment across different frequencies, which is the limitation of 5G networks.

4.1.4. Disintegration and virtualization of the communication networking devices

The inflexible and rigid networking devices have initiated to transmit in the direction of disintegration in recent years. Present 5G networks were not able to solve the challenges and issues in networking, such as challenges related to the design of disintegrated architectures and providing privacy and security of virtualized network functions. These disintegrated networks would help and work under the higher control latency that might be introduced by centralization. It is believed that 6G networks will solve these issues and challenges by providing disaggregation to the utmost by virtualizing physical layer and medium access control layer equipment [25]. All these functions operate if proper hardware execution and less-expensive, affordable, and diverse policies with minimal processing cost. Thus, 6G would help to lessen the expense of networking components, which makes the deployment of large networks economical.

4.1.5. 3D network architecture

5G and other generation networks have been structured and deployed to provide connectivity in bi-dimensional space (for devices on the ground). But, we expect that the next generation 6G heterogeneous networks to provide 3D (three-dimensional) coverage, which includes aerial & space networks (e.g., drones, satellites, and balloons) along with terrestrial networks. This would ensure low-cost seamless service with high reliability in events as well as in rural areas where fixed infrastructure is not available [78].

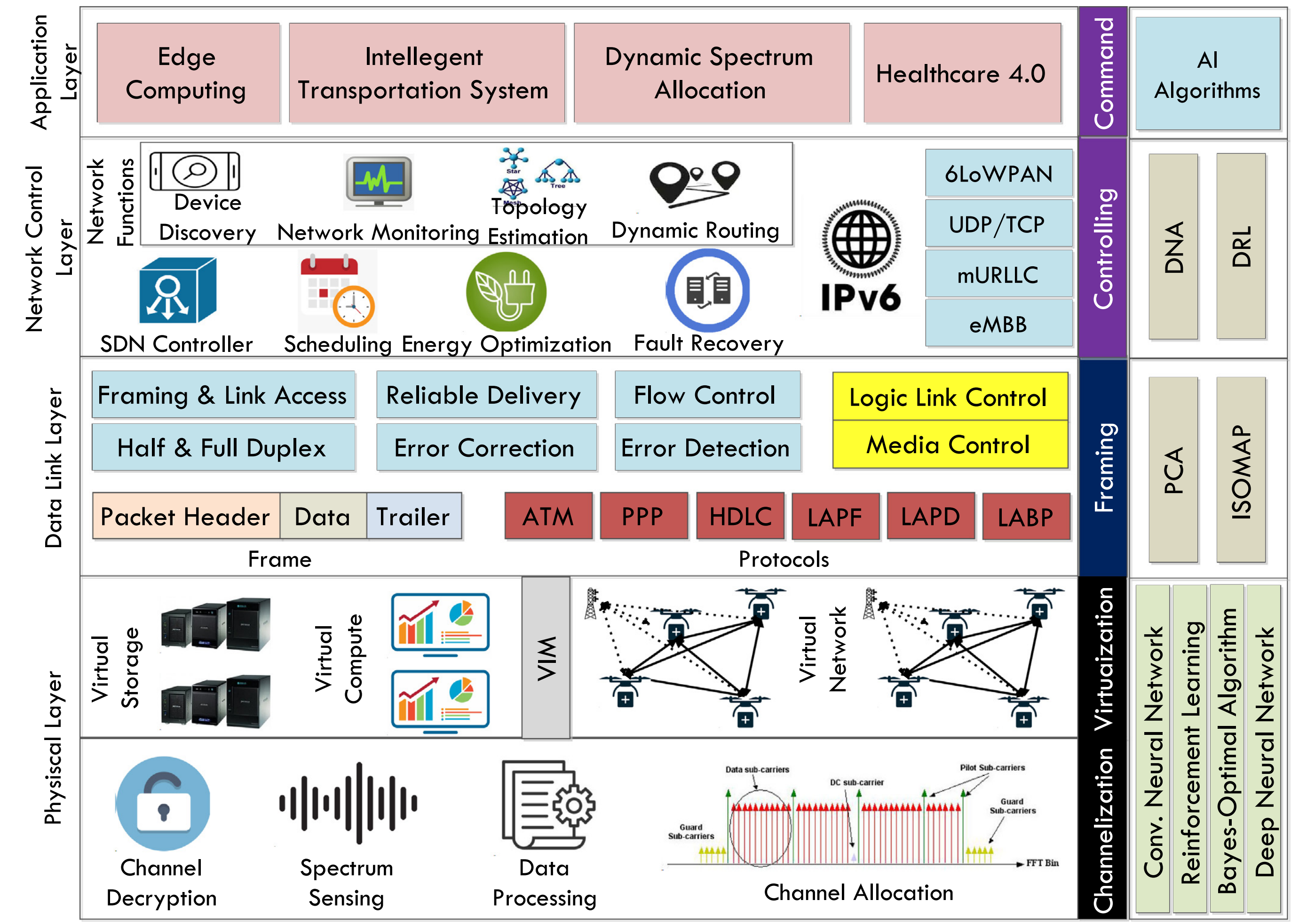

Fig. 4. Proposed AI-based 6G Architecture [24,77].

In spite of optimistic opportunities, few challenges are required to be solved before implementing it. The altitude of low orbit satellites is *700–1500* km, the ultra-low delays are difficult to achieve due to large distances between satellite and the earth. The large distance also needs a high power requirement for IoT devices to communicate with the satellite. For frequent data transmission from IoT devices, data aggregators can be deployed. The data aggregator can collect data from IoT devices in their coverage area using terrestrial communication technologies and then transmit all data together with space communication [17]. As the aggregators will be less in number, they can be managed and their batteries can be wirelessly recharged using UAVs (unmanned aerial vehicles) or replaced manually [79]. Thus to achieve all goals using this architecture, it is required to enhance work on air to ground channel modeling, energy efficiency, topology and trajectory optimization, and resource management to get better results [25].

4.2. AI-based 6G architecture: Proposed solution

In this section, we discussed the proposed AI-based 6G architecture layer-wise starting from the bottom physical and MAC layer and moving upwards to the data link, network, and finally, the application layer. For each of the layers, we discussed how AI can be incorporated and which functionalities of the layer it can enhance. Our proposed architecture is given in Fig. 4.

4.2.1. AI at physical and Medium Access Control (MAC) layer

This networking layer is considered as the foundation layer, where important technical implementations have been functioned. The various functions at this layer which, when integrated with AI, will perform their tasks in the better way are discussed below:

- *Allocating Channel Estimation*: It is censorious for MIMO operations to have proper and complete channel state information (CSI) available at the base station. Pilot signal allocation for deriving the complete CSI has become a difficult task from control overhead perspective in massive MIMO. To reduce this overhead, various approaches and standards reduce the number of pilot signals to be significantly smaller than the number of antenna ports. To solve this channel estimation issue, AI techniques have been integrated with the physical layer. For instance, Neumann et al. [80] presented an innovative technique to learn the low overhead and low complexity channel estimator. This was influenced by the structure of the MMSE estimator. There are no model parameters that have to be fine-tuned for different channel models. CNNs were used as the learning model and the learned estimator is optimized for some idealized channels [80].
- *Processing of Received Data*: MIMO symbol detection plays an important role in the parallel signal processing chain of communication receivers. MIMO has become the mainstream field in wireless communications because of its help in increasing spectral efficiency and link reliability, efficient MIMO symbol detection algorithms also play a critical part in receiver design, and various

research is conducted in this field [81,82]. For instance, let us assume that receiver CSI is available, we need an efficient and optimal strategy for placing the maximum likelihood detector. Nonetheless, the performance of this maximum likelihood detector is not encouraging as the performance is highly dependent on model inaccuracies and CSI estimation errors. To overcome this problem, AI techniques can give better performance without depending on detailed channel models. Hengtao et al. [83] developed a novel model-driven DL Bayes-optimal signal recovery algorithm for detection and provides good performance. It shows that deep learning can improve the iterative algorithm by optimizing some parameters. Various other works show that through end-to-end training of neural networks, AI models can outplay the traditional MIMO detection approaches (Maximum Likelihood) [84,85].

- *Dynamic Spectrum Sensing and Access*: Proper and complete access to the spectrum is going to be a censorious task for 6G networks. Spectrum sensing is an important task to improve spectrum usage efficiency and address spectrum scarcity problems. Current state-of-the-art techniques design the spectrum access protocols for specific models so that the difficulty in accessing the spectrum can be reduced. Nonetheless, spectrum sensing is the most challenging as a quite large number of devices try to access the spectrum at the same time, and also due to the inharmonious nature of future cellular networks, the solutions which are dependent on the model cannot be implemented in real-time conditions. So, the learning-based random access and dynamic spectrum access strategies can be used to solve the problem of spectrum access to these large numbers of devices [86]. These AI-based approaches help in identifying the spectrum properties and also helps in building applicable training models to sense the working of the spectrum. Deep Reinforcement learning-based strategy is provided in [87], showing that devices learn near-optimal spectrum access strategies without prior knowledge of the underlying network statistics. AI-enabled learning models detect the spectrum working status by categorizing each feature vector into either of the two classes, namely, the spectrum idle class and spectrum buy class, and adaptively update the learning models bases on dynamic environments.
- *Channel Decryption*: Channel decryption is also an important part of physical layer transmission. To make it efficient, AI techniques are used either as an integrated or stand-alone manner. Deep learning-based neural networks are much popular for channel decryption. They can be utilized in two diverse ways as — DNNs in combination with traditional approaches for obtaining performance gains and the other way is the stand-alone strategy to perform close to Maximal Aposteriori Probability (MAP) decoding for short block length communication [88]. Gruber et al. [89] achieved to decode polar codes along with random codes with MAP performance but has many limitations. They got a surprising result with neural networks. It is of great importance as state-of-the-art polar decoding suffers from high decrypting complexity, proper parallelization, and at last, poor latency. Thus, deep learning-based decrypting is a great substitute as it neglects sequential algorithms [90].

4.2.2. AI at data link layer

This layer aims to process and analyze the large amount of data coming from the physical layer of 6G networks. This collected data can be heterogeneous and can have multi-dimensions and non-linear. So, it makes the processing task complex and put other challenges too. It is quite expensive to store such large data in higher and dense layers of networks. So, the important task of this layer is to lessen the dimensionality of collected data, filter the needed and valuable data from available unfiltered raw data. AI techniques such as PCA and ISOMAP are the frequently used techniques that allow 6G to do this difficult task of converting raw data to proper and usable data [91]. The other advantages of these approaches over the conventional ones are the decrease in computing time, storage space, and model complexity. Data analytics is also responsible for analyzing the data collected to find the needed information and knowledge. The main task of the analytic sub-layer of the data link layer is to provide an appropriate explanation for resource management, protocol adaptation, architecture slicing, and signal processing.

4.2.3. AI at network layer

The unceasing increase in data traffic implies the need for smart agents at the network layer to smartly plan, optimize, and choose the most suitable action after utilizing appropriate knowledge from the previous layers. The combination of AI with a 6G network can help networks to achieve self-configuration, self-organization, self-healing, self-optimization, self-Sectorization, and fault recovery. Thus, it will lead to increase feasibility, reduce recovery time, and to provide improved service quality to the end consumer. The above-mentioned aspects of using AI at the network layer in 6G architecture is discussed below:

- *AI based Energy Optimization*: Instead of the traditional computation method, network parameters and architectures can be optimized with AI techniques. AI in 6G architecture can help to achieve intelligent softwarization, virtualization, cloudization, and slicing. For instance, different virtual network functions can be started, modified, or terminated in different virtual machines on-demand using a network management [24]. Data centers host the servers and virtual network functions and their services can be migrated from one server to another. By taking AI managed data centers into account, we can learn the patterns for the usage of services (which includes CPU, storage, and network usage) of the clients. This collected data can help to optimize the on-off operation of the servers and to close some servers to save power while ensuring uninterrupted services for the clients [92].
- *Fault Recovery*: Every system has to undergo a performance report and this data reflects the behavior of the system by providing service accessibility, service availability, service quality, service retain-ability, and service mobility. The abnormality in the system is required to be detected and resolved. Here, experts from the particular domain are required for problem detection, diagnosis, and problem recovery when we try to solve the problem using manual troubleshooting [92]. But, thousands of faults can be found at the same interval of time is common in current networks, human experts can manual troubleshoot it is non-trivial. An AI-driven fault recovery system can analyze pre-processed data using a deep network analyzer and can take remedial action on its own to solve the anomaly [93]. Thus, AI techniques can help to make system self-healing in 6G architecture.
- *AI for Scheduling*: Scheduling plays a vital role in the operation of cellular networks. With the increase in innovation and usage of IoT devices, cellular networks will not only have to be employed for human users, but they will also have to consider the thousands of low-power IoT devices. But, when coming to sensors, they are needed to sense for a limited amount of time and relay the measurements and then stopped. Thus, AI technology can be used to analyze the traffic from the sensors and decide the number of radio resources to allocate. A deep reinforcement learning algorithm can be used to learn and make a better decision over time to provide better results over traditional methods [94].
- *Self-Tuning Sectorization*: MIMO system is one of the foundations for the current generation of cellular networks [95]. It is a technique that coherently combines signals generated by multiple antennas to enable simultaneous beamforming, hence achieves a tremendous throughput gain and reduces interference. Actually, sectorization can be considered as the process of generating an expansive beam where a separate wide beam is used to

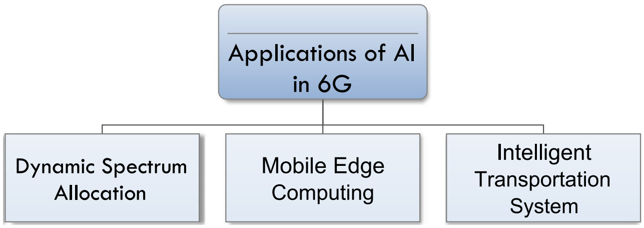

Fig. 5. A solution taxonomy for the selected applications of AI.

cover a separate sector. This sector-specific method of generating accurate beam patterns is necessary to maximize the network coverage. At the moment, broadcast beam parameters are set manually by the engineers and remain unchanged for years till major complain or fault is detected. Thus, this method cannot update itself on the basis of the user's position and movement. A deep reinforcement learning algorithm can be introduced to optimize broadcast beams for cellular networks dynamically. This method can be used to autonomously update beam parameters by studying user's distribution in the area, thus maximizing network coverage [96].

4.2.4. AI at application layer

Integrating 6G with AI can provide a new smart application or incorporate new services to an existing application to make it better. One such example is the usage of AI techniques in mobile edge computing can lead to the efficient computing power of edge devices so that every data is not needed to send to remote servers. This would till lower latency, which is necessary for real-time applications. Another such application is dynamic spectrum allocation where various AI algorithms like KNN, LSVM, RNN can help to allocate resources so that the overall network can work more efficiently. Another application is an intelligent transportation system where various AI techniques could make communication and networking in these systems better. There are many other applications where the introduction of AI with 6G networks could make existing systems more robust. The above mentioned three applications are mentioned in detail in the below solution taxonomy.

5. Solution taxonomy: AI techniques for 6G networks

This section discusses the taxonomy of AI for 6G application areas. Fig. 5 shows the proposed work considers the three major application areas of 6G where the AI can play an important role. Such application areas are dynamic spectrum allocation, mobile edge computing, and ITS. The detailed description of these applications is as follows.

5.1. Dynamic spectrum allocation

Due to the vast number of devices over the 6G, the spectrum must be allocated intelligently for the best optimum utilization. High-frequency bands can be allocated to the high-volume data, whereas for short messages low-frequency bands can be used. Another tactic to be used is dynamic spectrum allocation, where the idle space of the primary users (users who are currently registered on the network) can be used by the secondary users (users who are not registered but want to access the network). Primary users are given more priority over the secondary users and the signal of secondary users does not interfere with the primary user signals. Various AI techniques that can be incorporated for the dynamic Spectrum allocation are shown in Fig. 6. The detailed explanation of such techniques are as follows.

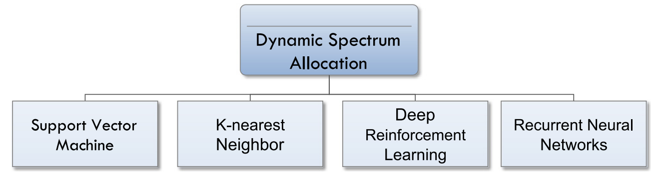

Fig. 6. AI techniques for dynamic spectrum allocation in 6G.

- *K Nearest Neighbor (KNN)*: New data value for instance a is assigned to a class by taking the nearest k neighbors after calculating the distance using a method such as finding the Euclidean distance. The class selected is the class which has the majority in the k neighbors. The value of k is mostly an odd number to get a clear majority every time. An example of KNN being used to allocate the spectrum in such a way that there is minimum collision/interference between different signals of low power and low range sources. In this method, the signal sources are classified into groups within which there would be a minimum signal collision between the sources. The classes used to group the same is based on the geographic location of the source and the interference distance of each cell [98].
- *Support Vector Machine*: It is used for binary classification with the goal to maximize the distance between samples of the different classes. Since secondary users uses the spectrum when the primary user is idle, we can use SVM to predict the primary user's traffic and then select the primary user with maximum future idle time and allocate it to the secondary user. It was found that the LSVM (linear support vector machine) is outperforming other techniques such as ANN, RNN, and GSVM (Gaussian Support Vector Machine) and could detect the traffic most efficiently [99].
- *Deep Reinforcement Learning with Reservoir Computing*: Reservoir computing is the specialized framework of RNN that works like a black-box and converts the input signals into higher dimensional spaces. Deep reinforcement learning is used to scout for the available spectrum bandwidth and the reservoir computing is used to generate the Q-Value by feeding in the spectrum information to the deep Q-network. After proper training of the network, each secondary user is able to make decisions with good accuracy regarding the spectrum access pivoting on minimum broadcasting information from the primary users. This combination of DQN + RC performs better than those methods relying on the spectrum statistics only [100].
- *Recurrent Neural Networks*: Maksymyuk et al. proposed a model based on RNN to dynamically manage the spectrum by taking into account the efficiency and the interference among the cells and also taking short and long traffic heuristics into consideration. This model achieved an accuracy of 90% and also was able to increase the network capabilities two folds [101].

The relative comparison of various AI techniques used in dynamic spectrum allocation is mentioned in Table 4.

5.2. Mobile edge computing

Mobile Edge Computing (MEC) is always a salient enabling technology for 6G architecture, which pushes computations to be performed as close to the devices as possible. Edge computing devices possessing both communication and computational capabilities are required to be kept near IoT devices from where data is generated. This will reduce the amount of data sent to the central computing servers which will eventually lead to lower latency, thus improving the performance of real time applications. This model will also provide high security as it would provide transient services through edge devices during network failure. In complex networks like MEC, AI techniques could provide better results rather than the use of traditional algorithms. AI techniques could learn and analyze the collected data and support in the task of prediction, optimization, and decision making in MEC [102].

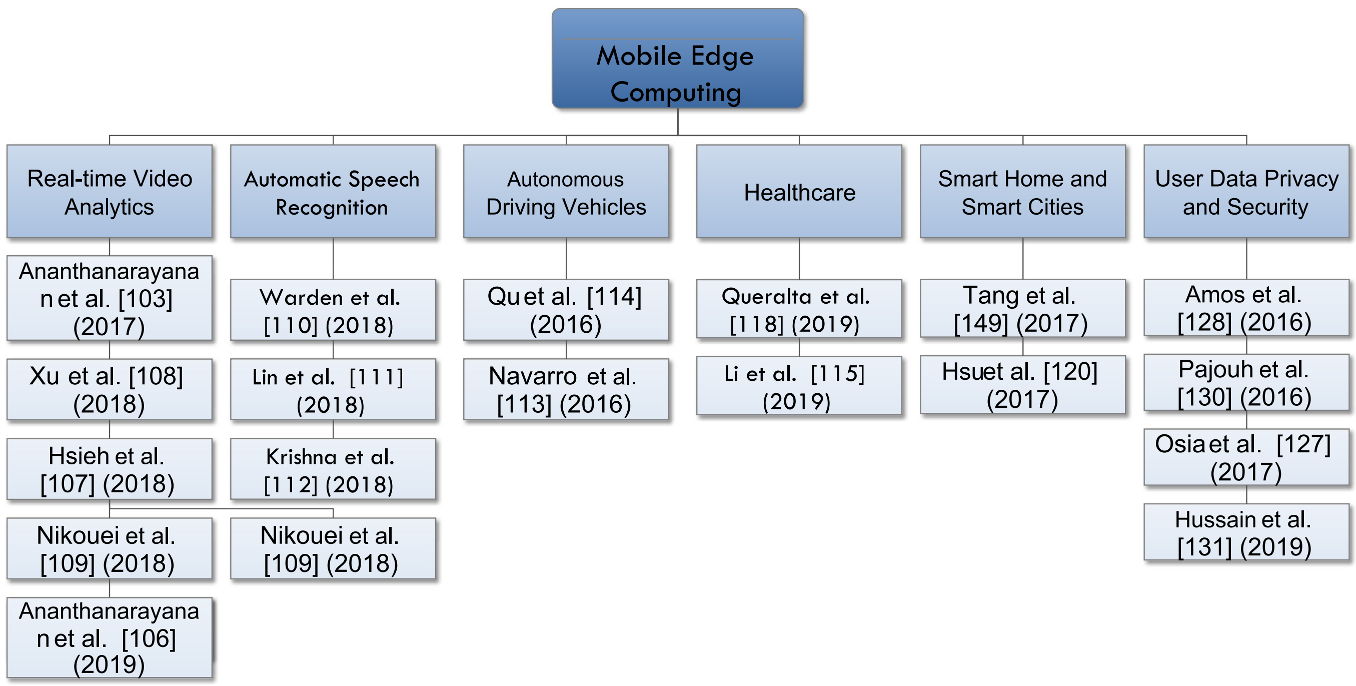

Fig. 7. AI techniques for mobile edge computing in 6G [97].

Table 4
A relative comparison of AI techniques used in dynamic spectrum allocation.

Author	Year	Objective	AI technique used	Merits	Demerits
Zhao et al. [98]	2018	proposed algorithm for interference-free spectrum allocation in small cell towers	KNN(K nearest neighbor)	Performed better (85%–87%) as compared to traditional mechanism(70%–75%) and VCG(50%–55%)	Used only geographical location of small cells and its radius as input features
Agarwal et al. [99]	2016	Explored various algorithms to predict primary user activities and idle time	ANN (RNN and multilayer perceptron) and SVM(Linear Kernel and Gaussian Kernel)	LSVM performs the best	Only works for a single primary channel
Chang et al. [100]	2019	Proposed algorithm for SU make its own decision based on past experience and current condition of the spectrum	Deep Reinforcement learning	Performs better than Q learning	Performs well only when number of channels is large
Maksymyuk et al. [101]	2019	purposed a model for spectrum allotment based on long and short term traffic information	RNN	accuracy of 90%	Better accuracy can be achieved if a large dataset is used

These AI algorithms can play an important role to provide high QoE in smart dynamic applications for edge scenarios. Some of the edge-based application where machine and deep learning methods plays an important role as shown in Fig. 7:

5.2.1. Real-time video analytics

Real-time analysis of video streaming is a significant role in a broad range of edge computing applications such as traffic safety and planning, augmented reality, and surveillance [103]. Real-time video devices are streaming data at 30 fps which is far better than previous systems which were processed at the rate of 3 fps [104]. AI integrated with Edge Computing and Internet of Things(IoT) cameras provides solutions for various problems and might comes up with improved services in real-time analytics [105]. Various research works have been done in this field in recent years.

One such work is done by Ananthanarayanan et al. [103], in which they developed an application named Rocket that develops high quality and high accuracy outputs with less expensive and quantity of resources. Their application collects and stores the videos captured from various cameras and decrypt it using vision processing modules. Modules have pre-built interfaces and application-level optimizations for processing and analyses of the collected data. Their application has a resource manager for implementing the data processing tasks on the different resource-constrained edge devices and cloud servers [103]. In [106], they presented the previous application Rocket in a variety of applications like a connected kitchen to pre-make certain most ordered menu dishes to reduce customer waiting time, traffic dashboard for raising an alarm in abnormal traffic volumes, and in the retail business for product ordering and placement.

In recent years, it is found that there is difficulty in finding the apropos video from a large dataset, as it is time-consuming and expensive. So, Hsieh et al. [107] developed a less-expensive low-latent video querying approach named as Focus. They implemented this approach using a GT-CNN, which is less expensive CNN architecture with small number of convolutional layers for identifying objects and indexing the classes of objects of real-time video streaming. Xu et al. [108] used SVM with Histogram Oriented Gradient (HOG) feature extraction algorithm at the edge devices to develop a real-time human surveillance system. They tested their model on the COCO image dataset having about 20k images and their model was successfully identifying the human and non-human objects in real-time. A similar kind of approach was also implemented in [109].

5.2.2. Automatic speech recognition

The use of this Automatic Speech Recognition (ASR) field in day-to-day life has been increased nowadays. Offline speech recognition system that supports digital voice assistant without using the cloud is also trending. Keyword spotting is one of the most used methods for offline speech recognition [110]. There are 3 important components of ASR:

- *Data Collection*: It collects the most suitable data available from the large quantity of voice data for speech recognition.
- *Feature Extraction Technique*: It extracts important and valuable features from the collected dataset.
- *Neural Network Model for Classification*: It uses extracted voice features as input to the model and obtains a possibility of each keyword as output.

Various researches have been incorporated in this field also in a few years back. For example, Lin et al. [111] designed a highly efficient Deep Neural Network (DNN) model which is known as EdgeSpeech-Nets to place deep learning models on communication devices for voice recognition. This model proved to be more efficient in terms of performance (accuracy of approximately 97%) and computational complexity than state-of-the-art techniques with a memory footprint of about 1 MB using Google Speech Commands dataset. One of the biggest advantages of this model is that it uses 36 times less mathematical operations resulting in 10 times lower prediction latency. The size of the network is also 7.8 times smaller than other models [111]. Another efficient model developed by Krishna et al. [112] was the first time that a deep learning model is demonstrated with high accuracy using only Electroencephalography (EEG) features for character or word level prediction. They created an ASR model using Gated Recurrent Unit (GRU) networks. They concluded that distillation training can improve the accuracy of an ASR system fused with EEG features.

5.2.3. Autonomous driving vehicles

Moving towards autonomous transportation, it is expected that it will offer safe traveling and improved traffic management. The number of sensors required to build autonomous driving vehicles is high and is also necessary that the data generated from them must be processed in real-time to make a quick decisions with high reliability (above 99.999%) and low latency (below 1 ms). It is difficult to transfer huge amount of data to remote servers and get feedback in real-time. Hence, edge computing becomes a necessary component in autonomous driving systems.

For autonomous vehicles, Navarro et al. [113] proposed a model for pedestrian detection on road. A LIDAR sensor was used to extract features like the movement of the object, stereoscopic information, and the appearance of a pedestrian which finally generated a n-dimensional vector. This feature vector was taken as input to run the machine learning model for autonomous vehicles and get 96.8% accuracy in identifying pedestrians. Another model based on deep learning and Retinex image enhancement was used to identify pedestrians in a short amount of time in real-time environment. YOLOv3 [114] deep learning algorithm were implemented on the COCOMO dataset and gave an average recognition rate of 94% for pedestrian detection. You Only Look Once (YOLO) algorithm will detect all the pedestrians in one go and hence it will be faster.

5.2.4. Healthcare

AI is being used by doctors and healthcare researchers to aide them in proving better patient care while keeping the accuracy high and cost low. It is being used in almost all aspects of healthcare such as reading medical images (e.g MRI, X-ray, etc.) and diagnosing the condition, using Natural language processing for speech-to-text and automatic documentation and development of more precision drugs which are tailor-made according to the patient's anatomy and not using the same standard drug for all.

A three-later hierarchical architecture was proposed by Li et al. [115] which is dubbed as EdgeCare. The bottom layer is the user layer tasked with data collection. With the advent of user wearable IoT devices capable of measuring user vitals at real-time. The real-time data along with the Electronic Medical report (EMR) of the patient are used as the raw data which are then transmitted to edge servers for analysis [116]. The next layer is the edge layer in which the entire network is divided into several constituent regions each with its own Local Authority. It is the responsibility of the local authority for the storage of uploaded data and to whom the data should be provided. In this layer, various tasks are performed such as user account management (creation and blocking it for suspicious behavior), storage facility, data prepossessing and analysis, and finally access control (to whom the data could be shared). The topmost layer is the core layer whose task is to ensure data and privacy security over the entire network. It also coordinates the working of the various local authority in a different regions of the networks. The presence of core layer refines the working of the entire system and ensures better coordination [117].

Queralta et al. [118] developed an edge-AI system for fall detection working over the LoRa network. The system reduced the processing at the sensor nodes and transferred the task to the edge nodes. Human vitals (e.g. EEG, EMG, etc.) and environmental readings (e.g humidity, temperature) are sent via Bluetooth to an edge node [119]. Primary processing is done at the edge nodes using AI and they can detect the fall with high accuracy. The results from these levels are send to the LoRa based access point where some advanced algorithms are applied and finally they are forwarded to the cloud servers for the final data processing. LSTM recurrent network was used and it achieved peak accuracy of 90.10%.

5.2.5. Smart home and smart cities

The emergence of IoT devices will bring intelligent systems such as intelligent lightning system, smart doorbell, smart appliances, and smart security system. To achieve this, several wireless IoT sensors and controllers are required. To ensure safety so that sensitive data is not used in wrong manner, it is necessary that data processing of smart home systems rely on edge computing. The combination of AI techniques with edge devices would help to make the use of intelligent systems more powerfully.

To ensure safety, a fall detection system was developed which would generate alert messages and notify users when an object falls. Here, Raspberry pi2 device is used as an edge computing device to process and reduce the size of images for real-time surveillance [120]. ML models work for extracting features on the cloud to detect the fall of the object and notify users whenever required [121]. The above-stated model can be improved by using deep learning model to consider only the foreground image for fall detection. It will eventually reduce traffic and save communication costs. Another deep learning model for load management in smart cities dubbed as DRUMS was proposed in which

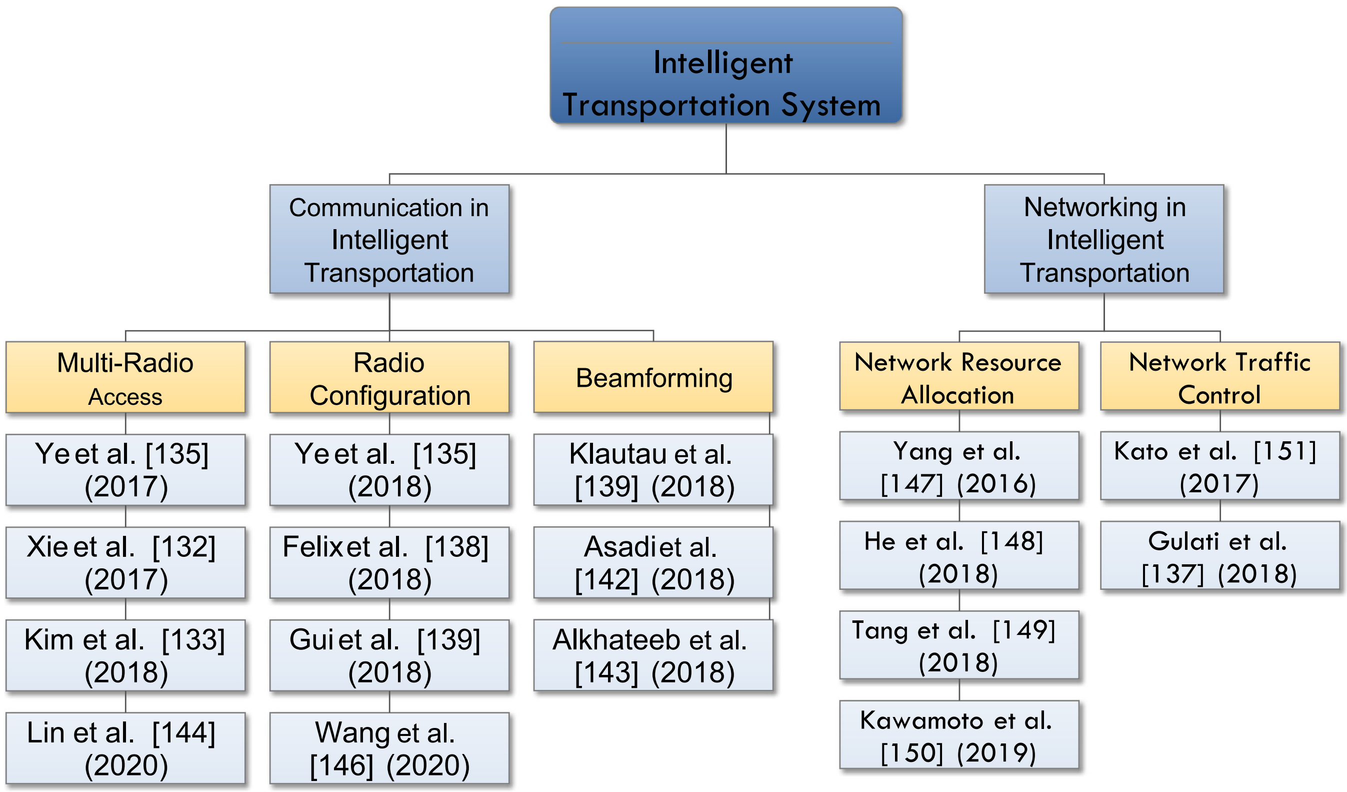

Fig. 8. AI techniques for management of ITS in 6G [19].

the analysis on the consumption data from smart homes was done using CNN. The main aim was to reduce the gap in the load supply and demand [122].

The edge computing-based model for the smart city would offer location-awareness and latency-sensitive monitoring and would help in reducing cost and increase efficiency. The hierarchical edge computing architecture was designed by Tang et al. [123] to analyze big data generated from millions of sensors attached across a smart city [124, 125]. The SVM algorithm was used to detect threatening events on the pipeline. The large numbers of sensors were used to collect data and this data was used by edge computing device to detect and avoid life-threatening events. For example, in case of gas leakage, the device would detect the threats and stop supply of gas to that particular smart home and thus reducing the risk. For this, SVM was used by the authors. Here, the data was sent to the remote servers only to compute complex calculations which would help to analyze and give better results if the same event repeats in the future. In this scenario, use of other deep learning models like LSTM neural network model could give better results with more efficiency. Another SVM approach was proposed by Jindal et al. [126] for the load management of the load imposed by hybrid vehicles and smart homes. Here, cloud technology was utilized for the usage analysis of the grid, and suitable regulations of demands were performed.

5.2.6. User data privacy and security

The global boom in user data is felicitated by social networking sites, mobile applications which are highly customized for each user and by IoT devices which are used in many sectors such as health care and home Automation. Such massive amounts of private data if leaked can be misused. To ensure that a user's private data is not exploited and sold to third-party data firms many security protocols can be implements and improved using AI. Osia et al. [127] developed the combined architecture consisting of cloud computing and edge computing in sync to ensure data security. Once the data is collected, it is then sent to the edge servers for processing the user's private and confidential information. Once this is done, the remaining non-trivial information is transferred to the cloud servers [127].

Another method using computer vision was designed in which user has the complete knowledge about cameras recording them, how the collected data is used. IoT Resource Registry (IRR) is a platform created for the IoT device owner, which helps them register the device on the platform, define the privacy policy for the same and to clarify for what reason the data collected will be used. A mobile application called IoT Assistant tells the user about the devices registered in the IRR and it gives the user an alternative to opt-out of data collection service. The user's privacy preferences are stored in the IoT devices and can be accessed again for future reference. It also includes a Face Trainer system which is based on deep neural network OpenFace which captures the features of the user's face. The network is trained using user-photos provided to IOT assistant mobile application. To ensure that good accuracy, users must upload a minimum of 20 photographs [128]. Privacy Mediator is a tool by which if a user wants to opt-out of the data collection service before the video gets transferred to the cloud servers, the faces of such users will be covered by a black rectangle box [129].

The above methods can be used from the user side to ensure privacy. The network must also detect malicious attacks and anomalous data. Pajouh et al. [130] proposed using the K-NN and naive Bayes algorithms to detect anomalous behavior. They trained the model on the NSL-KDD dataset and were able to verify that an edge device can detect such behaviors [130]. Hussain et al. [131] developed a deep CNN based architecture achieving peak accuracy of 96%. A central anomaly detection system can get overwhelmed by the amount of data in the network and might not give maximum performance. To circumvent the problem, the network was divided into 100 non-overlapping regions each equipped with its own edge server dedicated to anomaly detection only. The relative comparison of various AI techniques to make mobile edge-based application is mentioned in Table 5.

Table 5
Comparison of various AI techniques used in mobile edge computing.

Application	Author	Year	Objective	AI technique used	Merit	Demerit
Real-time video	Ananthanarayanan et al. [103]	2017	Proposed a real-time video analytics system for traffic planning and safety	DNN	Provided high accuracy outputs with low costs using the software named "Rocket"	Less use-cases provided by the system
	Hsieh et al. [107]	2018	Proposed a system to process the queries on large video datasets efficiently	Ground-Truth CNN (GT-CNN) (e.g. YOLO)	Provided both low-cost and low-latency querying with cheaper CNN than other approaches like NoScope	Only applicable for video dataset and not the audio, geo-informatics and bio-informatics
	Xu et al. [108]	2018	Developed a smart surveillance architecture to facilitate the on-site, real-time video processing	HOG + SVM for human detection and KCF algorithm for object tracking	Experimental results outperformed other approaches towards a real-time surveillance solution of edge networks	Their detection algorithms were expensive and system was not as efficient as needed for real time video surveillance
	Nikouei et al. [110]	2018	Explored the workability of current-of-the-art and developed a novel model for smart surveillance system	Light-Weight CNN	Developed an efficient system for human detection having average FPS of 1.79 and with less memory	Still some challenges were not fulfilled
	Ananthanarayanan et al. [106]	2019	Proposed an improvised version of real-time video analytics system developed in previous version [103]	CNN	More advanced approach and more use-cases than the previous one	Approach utilized needed more efficiency for general use.
ASR	Lin et al. [111]	2018	Proposed EdgeSpeechNets model based on DNN for voice recognition	DNN	Used 36 times less mathematical operation which resulted into 10 times lower prediction latency	This model strategy is required to be explored on different datasets of speech recognition to validate the results
	Krishna et al. [112]	2019	Proposed a novel model for efficient speech recognition	Deep Learning based distillation training using EEG features	First time deep learning was used with EEG features	Approach needs to be improved for general use
Autonomous driving	Navarro et al. [113]	2016	Proposed method for autonomous vehicles to detect pedestrians	KNN, Naive Bayes and SVM	Achieved 96.2% accuracy	Algorithm is computationally heavy
	Qu et al. [114]	2018	Proposed system for pedestrian detection after enhancing low quality images	YOLOv3	Algorithm performs algorithms without enhanced images	Good detection rate only when the number of single pedestrian images less than 25
Healthcare	Li et al. [115]	2019	Presented a efficient system for mobile healthcare systems	Hierarchical model for system named EdgeCare	Elaborately designed the system with secured and efficient data management	Some challenges were compromised
	Queralta et al. [118]	2019	Proposed a system architecture that combined AI with Edge computing and health monitoring	LSTM-RNN	Achieved better accuracy in implementing this combined system than traditional approaches	Not capable of high extensive performance and improvements were needed

(continued on next page)

5.3. Intelligent transportation system

ITS is an innovative application that provides the user with all information on the prevalent conditions in multiple modes of transport and helps them stay safe and well informed. It also aids in traffic management. The bifurcation of ITS is based on communication and networking aspects of 6G as shown in Fig. 8. In this section, we discuss the applicability of AI in the transport networks.

5.3.1. Communication in intelligent transportation

Communication in ITS has been a trending research topic since the last few years. Communication among the vehicles and also among

Table 5 (*continued*).

Application	Author	Year	Objective	AI technique used	Merit	Demerit
Smart home & cities	Hsu et al. [120]	2017	Fall detection system for smart home	Deep learning	Reduced traffic and save communication cost	This model is still under development and has not been implemented
	Tang et al. [123]	2017	Proposed algorithm for smart pipeline monitoring in smart city	SVM	Provide high computing performance, low latency and intelligence in smart city	Use of LSTM could give better results with more efficiency
Data privacy and security	Pajouh et al. [130]	2016	Detect Malicious attacks and behavior	KNN and naive Bayes	Performed better as compared to traditional methods	Detects attacks only in the backbone layer only
	Osia et al. [127]	2017	Proposed algorithm to split large neural networks	Deep learning	Increased user privacy	Hyper-parameters can be optimized
	Das et al. [129]	2017	Created an application which gave the user complete control over the data being collected via cameras	Computer Vision and Deep Neural Network	Gave an option to users to opt out of the data collecting process	Application requires the user to upload 20 pictures of themselves for better accuracy
	Hussain et al. [131]	2019	Proposed a system to prevent the network being overwhelmed by massive amounts of data	CNN	Achieved peak accuracy of 96%	Each one of the 100 divided regions needs to be equipped with its own edge server which increases the overhead costs

other roadside infrastructure is vital for the introduction of intelligence in transportation systems. Bluetooth, WiFi, Zigbee, and other communication protocols were used to establish communication between the vehicles. But, these techniques came with a certain limitations such as lack of sufficient flexibility, high power consumption, collision avoidance issues, and so on. These limitations were barriers to the advancement of transportation systems. So, in recent years, much research is incorporated on how to integrate AI in this field. In this section, we have discussed AI integration in three sub-parts of communication based transportation as shown below:

- *AI for Multi-radio Access (MRA) and Channel Division*: Nowadays, rapid access to multiple radios and precise channel division has become a necessary requirement for communication networks. Various technologies like Orthogonal Frequency Division Multiplexing (OFDM), Time Division Duplex (TDD), and Non-orthogonal Multiple Access (NOMA) are extensively used for channel estimation for multi-radio access in communication networking. But, these traditional technologies were not able to meet the high standard requirements of the transportation systems. Thus, it is believed that by integrating AI with this communication-based transport system will solve these limitations. So, various noteworthy contributions have been made by various researchers in this field. Different AI techniques like SVM, MLP, Bayesian Learning, KNN, DNN, LSTM, and Q-Learning are incorporated in this transportation system for the last 10 years. Xie et al. [132] developed the MRA network switching problem as an Markov Decision Process(MDP) and solved the MDP problem using value iteration algorithm. They took into account a scenario where Multi-mode Mobile Terminals (MMT) in a heterogeneous network environment can connect to multiple networks at the same time. By implementing MDP, they achieved higher average utility function value and the throughput requirement for networks with higher probability which is far better than the

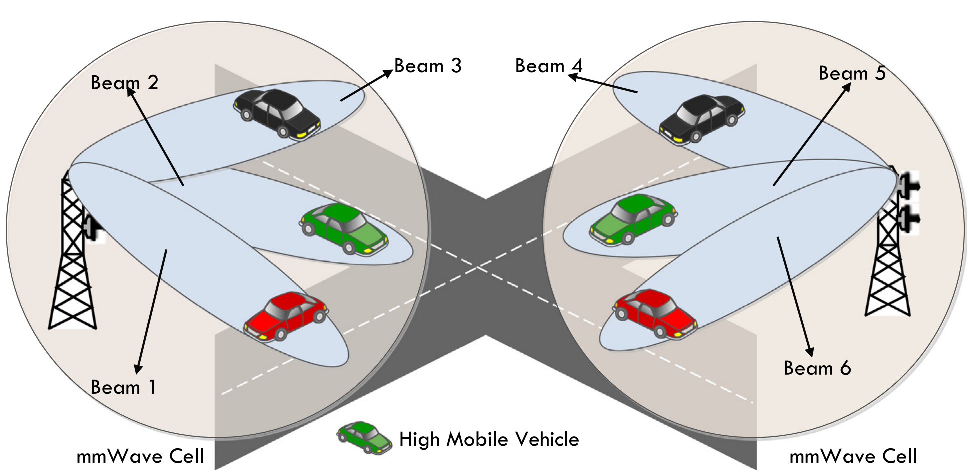

Fig. 9. Illustration of dynamic beamforming in vehicular network [19].

previous state-of-the-art approach named Greedy Method. The average switching time for MDP is *2.42* which is far better than the switching time of *11.46* for greedy method.
Another approach of using Sparse Code Multiple Access (SCMA) which was integrated with deep learning was used by Kim et al. [133]. They proposed a D-SCMA approach in which an autoencoder based structure was implemented in the generation of codewords and the determination of decoding strategy. DNN helped in mapping data to resource and decoding the received signal. There are many advantages of using this approach such as decoding can be done here in a single shot, which could only be possible by executing several iterations using cyclic belief propagation in traditional SCMA, also D-SCMA provides lower bit error rate and lower computational complexity than the traditional SCMA.

- *AI for Radio Configuration*: In the past years, when the traditional communication system was introduced, radio configuration was taken into consideration as decoding blocks for space–time codes, channel equalization, and also for signal modulation. These blocks were shredded with separated communication functions, and the configuration of radio was done in a progressive approach as a functional chain [134]. The Channel resource allocation algorithm must be developed by taking into consideration the different modulation signals. There are certain limitations of this approach as it is time-consuming and it is not applicable for highly complex dynamic transportation systems. It is a challenge for 6G networks to overcome these limitations. By taking AI into effect, it might solve these problems. To address these challenges, researchers proposed various AI-based adaptive configuration algorithms to optimize these blocks for radio configuration.
Ye et al. [135] demonstrated an offline DBN based model for channel estimation and signal detection in an OFDM system. The results showed that deep learning has advantages when wireless channels are complicated by serious distortion and interference. So, it was proved that DNNs are capable of remembering and analyzing the complex and challenging properties of the wireless channels [135,136]. Mendis et al. [137] introduced an Automated Modulation Classification (AMC) for cognitive radio. Their proposed architecture included a Spectral Correlation Function (SCF) based on the feature characterization mechanism, which was used to generate SCF patterns that characterize the features of the modulation techniques involved, and DBN based identification scheme having DBN to classify the modulation techniques by learning their features from the SCF patterns. They concluded that their approach achieved high accuracy (above 90%) even with the involvement of environment noise [137].
Another novel DL based approach was proposed by Felix et al. [138], in which they implemented autoencoder for OFDM which configured the channel without using traditional signal processing block. Gui et al. [139] proposed an efficient and high performance based DL-aided NOMA scheme. Using Restricted Boltzmann machines (RBM) and LSTM network, their scheme could model the spatial–temporal relationship between input signals and the sharply changing channel conditions by learning the environment automatically via offline learning. Their model was far better than previous state-of-the-art methods in terms of BLER and sum data rate, robustness, and high precision rate [139].
- *AI for beam-forming*: With the advancement in communication technology, it is believed that, in the near future, the *mmWave* will be extensively used. Observing the current extensive use of beam-forming and massive MIMO technologies, it is desired that it would provide great advancement in specific high-dynamic transportation communication systems [140]. But, for building the *mmWave* in these high-mobility systems are using traditional beam-forming techniques, the beam-forming accuracy got affected by vehicle location predictions and high overhead of frequent beam training [141]. Fig. 9 shows these limitations. In order to build proper and efficient *mmWave* and the respective strategy for beam-forming, AI might be able to solve these barriers. Few recent pieces of researches are shown below:
For high-dynamic transport systems, data regarding out-of-band measurements and vehicle positions becomes a barrier in forming the best beam pair selection time. So, in [140], Klautau et al. developed a DL based beam selection algorithm after executing various algorithms and based on the observation that this DL based approach is far better than other algorithms in terms of accuracy for classification and root mean squared error for regression. Another approach was proposed by Asadi et al. [142], where they implemented the ML-based algorithmic system by which the coarse user location can be involved in dynamic beam selection for sensing the changing environment. It had improved the performance and stability of communication networks. Alkhateeb et al. in their paper [143], considered that the overhead of beam training must be in accordance to the need of generating *mmWave* and proposed a novel DL based beamforming algorithm for the specific high mobility *mmWave* system. They concluded that using this approach, reliable coverage, low latency, and less training overhead have been achieved.

The comparison of various AI techniques used in the communication field of intelligent transportation systems is mentioned in Table 6.

5.3.2. Networking in intelligent transportation

The issues faced during the networking of ITS is resource allocation and traffic control this section, we discussed existing solutions for the aforementioned issues using AI techniques.

- *Role of AI in Network Resource Allocation*: The proper allocation of wireless network resources including channels, computational capacity, power level, and time slots is difficult because of unpredictable user requirements. Apart from a standard wireless network, the vehicular wireless network requires heterogeneous structure, high mobility nodes, and high QoS for both passengers and drivers (in case of a not fully autonomous vehicle). To implement the conventional resource allocation algorithm like auction theory, greedy algorithm, and game theory on vehicular wireless networks faces some challenges.
In the field of autonomous transportation, resource allocation is necessary for decision making to be responsive by allocating resources rapidly even in changing environments to overcome signaling overhead, provides accurate results to avoid accidents even in a complex environment, and also self-adaptive. One model for dynamic resource allocation problem was proposed by Yang et al. [146] where they employed graph coloring theory to ensure the accurate environment modeling in VANET heterogeneous networks. But, this proposal was not able to address the problem of self-adaptability and was even time-consuming. Many other conventional algorithms also failed to provide good efficiency in a vehicular network, but many new emerged ML technologies can be able to solve the problems for future vehicular networks in 6G. Due to the special constraints of the vehicular network, various AI-based models for dynamic resource allocation are proposed for 6G network.
He et al. proposed model for next-generation vehicular network considering radio, caching, networking, and computing resources based on DRL. Considering virtualization and centralization, a new resource allocation strategy was formulated for multiple tasks joint optimization problem [147]. The use of two deep learning models CNN and DBN together was suggested in [148] to predict asynchronous traffic and to assign the channel to links intelligently. Using CNN, traffic patterns were learn online, analyzed and trained to predict the future traffic levels for any

Table 6
Comparison of Various AI Techniques used by existing works in the Communication field of ITS.

	Author	Year	Objective	AI technique used	Merit	Demerit
Multi-radio Access (MRA)	Xie et al. [132]	2017	Developed a MDP to solve the switching problem in MRA network	MDP	MDP achieved better results than greedy approach	Some work can be done to improve this algorithm for 6G networks
	Kim et al. [133]	2018	To minimize the BER, proposed a DL based SCMA	DNN	Showed lower BER with less computational time than traditional scheme	More improvements are needed for implementing with 6G networks
	Ye et al. [135]	2017	Proposed a DL based scheme to improve the reliability of grant-free NOMA	Multi-loss function based DL-aided grant-free NOMA	Lessen the human crafted work and enabled the automatic system which performed better than conventional NOMA	Low power consumption and high-reliability requirements were not considered
	Lin et al. [144]	2020	Proposed a model to decode SCMA modulated signals corrupted by additive white Gaussian noise	Deep Neural Network named DL-SCMA	Better performance compared to traditional SCMA	Not compatible in real environment system
Radio configuration	Ye et al. [135]	2018	Proposed a DL model to address the channel distortion	DNN	The model could remember and analyze the complicated characteristics	Rigorous and more comprehensive experiments were not conducted
	Felix et al. [138]	2018	Implemented autoencoder for OFDM	Autoencoder	Configured the channel without using traditional signal processing block	Novel approach but the performance was not up to the mark
	Gui et al. [139]	2018	Proposed a DL-aided NOMA scheme	RBM-LSTM	Efficient, high performance and better than previous state-of-the-art	Not compatible in real environment system
	Wang et al. [145]	2020	Proposed a DL model for MIMO systems	CNN based Co-Automatic Modulation Classification	Performed better than HOC and ANN-based traditional methods	Future challenges were not considered while proposing the method.
beamforming	Klautau et al. [140]	2018	Proposed an application for Beam-Selection	Deep Learning based model	Generated 5G propagation channel data that decouples the tasks of modeling mobility and channel	Computational Cost was high and lack in accurate modeling.
	Asadi et al. [142]	2018	Proposed a lightweight context-aware online learning algorithm to address the problem of beam selection	FML based algorithm	Improved performance and stability	Integrating DL would perform better
	Alkhateeb et al. [143]	2018	Developed an integrated ML and coordinated beamforming strategy for enabling mobile applications in *mmWave* systems.	DL based algorithm	Ensured reliable coverage and low latency	Further improvements in the model will perform better

hour of the day. From the results of CNN, the DBN algorithm is implemented to intelligently allocate channels. The Deep Belief network (DBN) used was already trained with existing data set from channel allocation algorithm.
Apart from ground vehicles, Kawamoto et al. studied Q-learning based intelligent resource allocation problem for unmanned aerial vehicles where communication demand and propagation environment are dynamically changing. The result from their study [149] suggest that their algorithm can adapt to various dynamically changing environment. Thus, by using machine learning and AI techniques in 6G network can help by making rapid response by decision making, estimation, recovery, and self-adaption of resource allocation in vehicular communication [152].

- *Network Traffic Control*: For high-dynamic vehicular networks, various domains like network routing, location, topology information, traffic offloading, and congestion avoidance are widely

Table 7
Comparison of Various AI Techniques used by existing works in the Networking field of ITS.

	Author	Year	Objective	AI techniques used	Merit	Demerit
Network resource allocation	Yang et al. [146]	2016	To ensure accurate environment modeling in VANET heterogeneous networks.	Used graph coloring resource sharing scheme	Their algorithm could achieve sub-optimal solution with low complexity	But the algorithm could not address the problem of self-adaptability and was even time consuming
	He et al. [147]	2018	To improve performance of future vehicular networks by improving caching and computing resources method	Deep Reinforcement Learning	The resource allocation strategy proposed for multiple tasks joint optimization problem has provided good results	There were energy efficiency problems in proposed framework
	Tang et al. [148]	2018	Proposed an algorithm to smartly avoid traffic congestion and allocate relevant channels to wireless links of SDN-IoT	CNN and DBN	Results showed that their algorithm outperformed conventional channel assignment algorithms	Some work can be done to improve this algorithm for 6G networks to make it environment independent
	Kawamoto et al. [149]	2019	Proposed intelligent resource allocation algorithm for unmanned aerial vehicles	Q-learning	Their algorithm could adapt to various dynamically changing environment	Still improvements are needed in the model for enhanced performance in resource allocation.
Network Traffic Control	Kato et al. [150]	2017	Proposed model to estimate traffic situation of whole network at edge level from collected data	DBN	Results showed that average per hop delay of their algorithm was lower than various conventional routing methods	Did not considered input features other than traffic patterns.
	Gulati et al. [151]	2018	Proposed content centric data dissemination scheme for vehicles	CNN and DBN	Ensures high data availability and minimum delay	Disconnection probability increases with increase in velocity of vehicles.

studied for network traffic control [153]. Considering above parameters, there is need to achieve ultra-low latency (<1 ms) and high data rate could not be solved even with the emergence of stability based adaptive routing, optimized link-state routing protocol, dynamic state routing, routing information protocol, and proactive source routing [154]. Machine Learning techniques could be used for future generation 6G vehicular network to improve dynamic routing and self-learning at the edge for congestion avoidance [155].
Location and safety information in a vehicular network is definitely going to be congested and even in remote areas, it is hard to pass complete global information timely. Thus, the model was proposed by Kato et al. [150] using deep learning algorithm. They used a DBN neural network and find co-relation between historical collected traffic patterns and routing decisions to estimate the traffic situation of the whole network. CNN based model was further proposed with optimal vehicle dissemination strategy and gradient descent process to ensure high data availability and minimum delay [151].

It is impossible for the current network to satisfy the requirements of vehicular networks like traffic control and resource allocation together. But, this can be made possible by including terahertz communication, VLC and intelligent AI techniques along with virtualization for the future generation 6G networks. The comparison of various AI techniques used in networking of intelligent transportation system is mentioned in Table 7.

6. Implementation issues and challenges

Although 6G is in the research phase right now, it shows great promise in terms of its network capability and diverse range of applications it can provide. However, it has not be perfected yet and it cannot be deployed in the current stage. The short-comings are as follows.

6.1. Frequency band

The teraHertz band will be used in 6G, which has a low wavelength. Due to this, the range of the signal will be hardly a few meters, and it is not economically justified to place a signal amplifier every few meters to circumvent this issue. Molecules in the air can absorb the signal and convert it to its kinetic energy, thus reducing range. This signal attenuation amplifies when there is moisture in the air, further shortening its range [156].

6.2. Device capability

6G enables unprecedented data speeds and the devices should be capable of utilizing it to the fullest. As far now, most of the devices are designed on the working principles of 5G, and they need to be designed in such a way that it can be used for 6G as well. Also, such devices cannot support all of the novel features of 6G, such as AI, AR/VR, high QoS, intelligent vehicles device sensing, and communication [157].

6.3. Big data

The data rate generation will reach exabytes in a matter of a few years. As of now, big data technology deals with large amounts of data from a single source, but not for small-sized data from various heterogeneous sources. The current infrastructure unable to handle so much data and we need supercomputers to process them. To accommodate such changes, we must make changes to the existing big data techniques [158,159]. Big data will leverage the principles of Iot and cloud computing to aid in data collection, its storage, and computation. Ray et al. [160] identified the potential security threats and shortcomings while leveraging such technologies. Changbo et al. discussed the potential challenges regarding the possible integration of 5G and big data such as security and privacy concerns in data sharing and data fusion and the requirement of real-time analysis of data [161]. Since 6G is an advancement from 5G, such challenges are expected as well.

6.4. Shortcomings in AI

Although AI is a technology with great potential, which has some shortcomings which are not resolved yet, AI works as a black-box in which we do not know how it works and why it takes a particular decision. In real-time scenarios, this can be a huge risk and potentially life-threatening in applications such as ITS. AI technology as it currently not given full decision making capability and must be used in congruence with the currently used proven techniques. There is no way of knowing whether the selected model and the data set in consideration will produce accurate results beforehand. Also, the model can perform well for one scenario but fail in for others. Different network service providers need to implement different AI models for their own individual needs, and they often are not in sync with each other, which can deteriorate network performance [162].

6.5. Edge communication

As discussed earlier, mobile edge communication will be one of the enabling technology of 6G. However, it has a few limitations as well. First of all, edge nodes are mobile devices that work on battery and have limited computing power, so most of the computing is done at the cloud, and the edge nodes are used only as an inter-mediator for communication. Edge nodes also are not capable of storing the excess information it receives and must transfer the data to the next layer as soon as it receives it; this increases the communication overhead. This reduces the 6G network performance.

7. A use case of UAV-enabled intelligent transportation system

A smart city has become a new buzz in current times for bringing new applications for making existing processes smart and better to improve the efficiency of future smart cities and the quality of living of the people. ITS is considered as one of the major building blocks of any smart city along with smart health care, smart governance, smart environment, and smart public services.

The 6G system can help in the deployment of autonomous vehicles and UAVs. Connectivity in ITS should be such that a vehicle can communicate with sensors, other vehicles, infrastructure, and even pedestrians [164]. With this type of communication system and usage of some advanced AI techniques, ITS can achieve safe intersection crossing, safe lane changing, optimal traffic signal control, smart parking allocation, and emergency warning notification. Unmanned Aerial Vehicle (UAV) plays an important role in 6G systems to provide a high data transmission rate and also support wireless broadcast in the areas where the cellular base station is not functioning or is absent as shown in Fig. 10. UAVs support certain features like line-of-sight links, easy

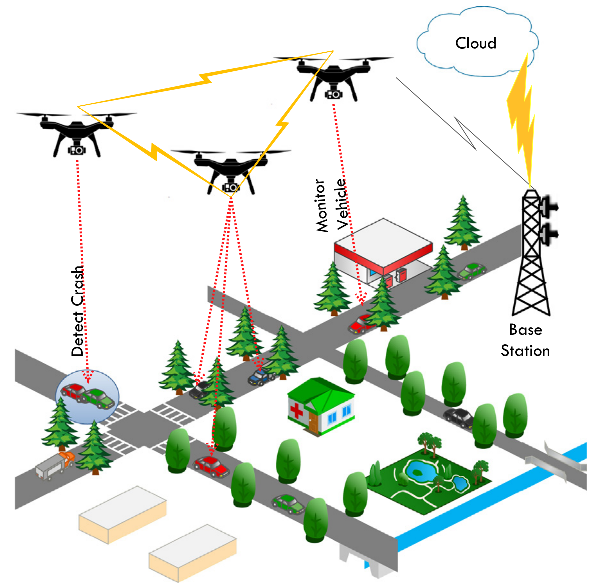

Fig. 10. UAV enabled ITS. [163].

deployment, and degree of freedom with controlled mobility, which cannot be achieved through terrestrial communication [165,166]. UAV can facilitate the main component of 6G wireless networks which are eMBB, mMTC, and URLLC and thus could help in various fields including military, science & commerce, aerial photography, surveillance, agriculture, and disaster management [167].

At the time of the disaster, UAVs are required to communicate with each other and to provide communication links for terrestrial devices. In place of traditional ITS, where communication was not possible in times of disaster, UAV enabled ITS could help to identify areas affected by disaster and also aid in disaster response. Due to the limited communication range, higher costs, and requirement of continuous connectivity, it is impossible to cover the area for a reasonable amount of time. Thus, it is required to increase energy efficiency using a deep reinforcement learning model [168,169] so that UAVs can keep flying and provide the network for a longer time.

In spite of having advantages in current ITS, there are various issues and challenges which have to be overcome using AI-based 6G future networks. The bandwidth limitation in the current ITS system is causing problems like communication interference, delay, and hence affects delivery efficiency in dense traffic scenarios [170]. The other challenge in current vehicular networks is the management of the data gathered from a huge number of vehicles congested with reduced distances at the same time and take actions on that collected data [171,172]. The current network is not equipped to handle this situation and thus causes delays and might also threaten the privacy and security of the user [173,174]. Also, the scheduling and channel allocation algorithms present in the current system are less efficient. There is decentralization characteristic existing in the current ITS, but still, in the current, ITS system vehicles connect and disconnect from the system at any time, and there is no fixed central system that ensures trustworthy communication between vehicles [175].

The above limitations in the current ITS can be overcome with the usage of our proposed architecture embedding AI techniques with 6G networks. The bandwidth problem can be eliminated by incorporating the VLC component present in 6G architecture. VLC gives the ultra-high bandwidth, which is the biggest advantage of 6G and we assume that more vehicles can communicate for a large period, which eliminates the bandwidth limitation of ITS. Also, the channel allocation problem can be solved by using CNN in our proposed architecture. The overhead and computation complexity will get reduced with the introduction of

CNN based algorithm. In the data link layer of our architecture, we have placed AI feature extraction techniques like PCA and ISOMAP, which reduces the overhead and computational complexity by eliminating the significant data. By implementing these techniques in current ITS, the flow of data in the communication channel between two vehicles will become easy and efficient. The current decentralization technique can be made more secure by designing a proper fixed system by integrating AI algorithms in 6G. Such a system would formulate a proper flow or directive for communication between decentralized vehicles. RL algorithm could help to manage resource flow among vehicles and also with the main system.

8. Conclusion

5G technology is expected to be fully deployed worldwide by 2023, but it will not be able to cater to the network requirements to the exponential increase in the number of users as well as would not be able to fully service all the functionalities that the full capacity. This growing demand of both users and functionalities requires 6G to be deployed as soon as possible. Research on AI about its application in the various domains is also being conducted and the results are promising.

In this paper, we explore the emphasis of AI integration in 6G, both in the application domain and the architecture domain, starting by discussing what AI is. The impact of AI is omnipresent in all the domains and 6G is expected to harness the full potential of AI techniques when it is gradually rolled out. We further proposed an AI-enabled 6G architecture utilizing various AI technologies starting from the physical layer and going all the way up to the application layer. Additionally, we discussed various possible applications that can be viable with such smart networks, having significant improvements over the traditional architecture by overcoming issues such as QoS, low latency provisions to the end-users. The study was further supplemented by presenting a use-case for UAV enabled ITS which fully leveraged our solution taxonomy methods. Finally, we explored the possible shortcomings and implementation issues in such intelligent networks and the applications that can be realized/refined with its help.

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.

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