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Machine Learning Techniques for 5G and Beyond

JASNEET KAUR[1], (Member, IEEE), M. ARIF KHAN[1], (Member, IEEE), MOHSIN IFTIKHAR[1], (Member, IEEE), MUHAMMAD IMRAN[2], (Member, IEEE), AND QAZI EMAD UL HAQ[3]
[1]School of Computing and Mathematics, Charles Sturt University, Bathurst, NSW 2678, Australia
[2]College of Applied Computer Science, King Saud University, Riyadh 11451, Saudi Arabia
[3]College of Computer and Information Sciences, King Saud University, Riyadh 11451, Saudi Arabia

Corresponding author: Jasneet Kaur (jkaur@csu.edu.au)

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ABSTRACT Wireless communication systems play a very crucial role in modern society for entertainment, business, commercial, health and safety applications. These systems keep evolving from one generation to next generation and currently we are seeing deployment of fifth generation (5G) wireless systems around the world. Academics and industries are already discussing beyond 5G wireless systems which will be sixth generation (6G) of the evolution. One of the main and key components of 6G systems will be the use of Artificial Intelligence (AI) and Machine Learning (ML) for such wireless networks. Every component and building block of a wireless system that we currently are familiar with from our knowledge of wireless technologies up to 5G, such as physical, network and application layers, will involve one or another AI/ML techniques. This overview paper, presents an up-to-date review of future wireless system concepts such as 6G and role of ML techniques in these future wireless systems. In particular, we present a conceptual model for 6G and show the use and role of ML techniques in each layer of the model. We review some classical and contemporary ML techniques such as supervised and un-supervised learning, Reinforcement Learning (RL), Deep Learning (DL) and Federated Learning (FL) in the context of wireless communication systems. We conclude the paper with some future applications and research challenges in the area of ML and AI for 6G networks.

INDEX TERMS Fifth generation (5G), sixth generation (6G), artificial intelligence (AI), machine learning (ML), deep learning (DL), reinforcement learning (RL), federated learning (FL).

I. INTRODUCTION

Sixth Generation (6G) is a new wireless technology that many academics and researchers are embarking on. The main promises of 6G are to extend AI and ML benefits in the wireless networks and to the users. 6G also will provide advances in technical metrics such as high throughput, supporting new high demand applications, improved usage of radio frequency bands and many more using AI and ML techniques [1]–[3]

One of the major ML technologies envisioned as a key technology for 6G will be DL because of its strong applications in achieving learning from scenarios which are more close to human. For example, DL can decide which access point to connect to in 6G and which resource controller has more resources available. It is interesting to note that DL has been being used successfully in classification problems and providing good results but what is the role of DL in wireless networks is still an unexplored area. In this article however, we provide an overview of broad categories of ML techniques including DL and their potential role in future 6G communication systems.

Wireless technology is continuously evolving and advancing in assisting to satisfy more advanced needs of users with more and more practical applications [4]. There is an upsurge in data rates, a reduction in energy consumption of devices connected with latency and energy in the 5G mobile communication system along with more accurate localization [2], [5]–[8].

Due to the current increase in data size and usage, many researchers have been surveyed that more focus should be on meeting latency and energy goals by enhancing the existing wireless system from different aspects. For example, deploying caching and computing resources at the edge of

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the network can meet the rising demands of low latency and reduction in consumption of energy [1], [9], [10].

Using large scale processing of signals among blind signal separation can provide high data rates in cloud computing, based on a Base-band Processing Unit (BPU) pool [11], [12]. This uses large scale processing that can further save energy through statistical multiplexing [13]. Additionally, the throughput of Device-to-Device (D2D) can be boosted with heterogeneous nodes that co-exist, including the Small Base Stations (SBSs) and User Equipment (UE). It also guarantees seam-less coverage [14].

However, the meticulous requirements of 5G cannot only be contented with presuming resources for computing and heterogeneous nodes, thereby indicating the value of progressive resource management, mobility management, networking, and localization. If the resources are appropriately utilized through the scaling network, then the performance of the wireless communication system can be improved [15].

Some (ML) algorithms cannot process or utilize meaningful wireless networks data in its raw format, thereby losing valuable information or patterns that can be used for wireless system modelling. The Radio Resource Management (RRM) algorithms are heuristic but complicated and hence cannot meet the performance requirements of 5G. Therefore, several researches have been evaluated to increase the reach of optimal or sub-optimal solutions for RRM algorithms to seek more effective solutions. However, high complexity can arise with developing algorithms due to complex network infrastructure and large scale in most 5G networks. Due to the lengthy decision-making process, existing RRM algorithms struggle to work effectively in a dynamic network such as 5G and 6G. The authors in [16] mentioned that due to a large number of nodes in 5G networks, it is infeasible to use centralized algorithms because of high computational power and enormous cost. Therefore, enabling network nodes to make a decision based on local observation is highly preferable. In such scenarios, if ML techniques are deployed at user level close to the edge of the network (Edge computing), the system can benefit from the nearby computations.

This article investigates ML-enabled intelligent 6G networks and highlights the research challenges associated with such networks. Then the article focuses on understanding ML and its behavior at the application level and infrastructure level. The article undertakes the consideration to meet the network capacity demand, high efficiency, low latency, minimum processing time, the security of communication system by comparing the performance matrices like power allocation, resource management, caching, energy efficiency, etc. at the application level and infrastructure level.

Main Contributions: The paper has following main contributions:

- The main research areas have been investigated in next generation wireless communication systems.
- The key concepts and techniques of ML have been reviewed.
- The connection between ML and 6G have been identified and discussed at application level and infrastructure level.
- A research problem for use of ML at application and infrastructure level has been discussed. Establishing a research problem for the use of AI at user and main infrastructure level.
- Future research directions have been highlighted in the domain of ML and 6G wireless communication systems.

A. RELATED WORK COMPARISON

Recently, a number of existing works such as [3], [17] and [18] have focused on analysing and studying important problems related to the use and implementation of ML over wireless networks. The authors in [19] stated that new generation wireless network can influence intelligent functions by integration with ML at wireless core and edge infrastructure. The authors in [20] focused on vision and research on 6G in coming decade. The authors deemed that the reality of 6G is ML and AI which need further investigation in layers of wireless communication model. This includes understanding signal processing in the physical layer, data mining at the network, etc. Further, the authors in [21] defined vision of 6G as complex network described by network edge, air interface and the user side. They further devised, the emerging paradigms of ML with communication networks can be considered as core 6G enablers.

Paper Structure: A conceptual flow diagram of the topics covered in this paper is shown in Figure 1. The outline of the paper section-wise is given as follows. In Section II, we present the background and motivation of this work. We also discuss the importance of role of ML and AI in future generation wireless communication systems. In Section III, we present a review of classical as well as contemporary ML techniques, their working principles and some of their benefits and limitations in the context of wireless communication systems. In section IV, we present current state-of-the-art in 6G technology, research challenges, future vision and potential 6G applications. In Section V, we present the use of ML at application and infrastructure levels and present a comparative study of ML techniques at these two different levels, i.e. application and infrastructure levels. This section also presents a case study on how AI and ML can be used at both application and infrastructure levels. Finally, Section VII concludes the paper.

II. BACKGROUND AND MOTIVATION

With the high expectations of top Quality of Service (QoS) and to support diverse applications such as real-time Virtual Reality (VR) applications from new wireless technologies, for example, 5G and 6G, researchers are tapping new frontiers of technologies for 5G and beyond wireless systems. For instance, massive MIMO (Ma-MIMO) and millimeter Wave (mm-Wave) technologies are considered as physical (PHY) layer technologies for 5G systems. Similarly, building upon 5G systems, new 6G wireless systems will have ML as their

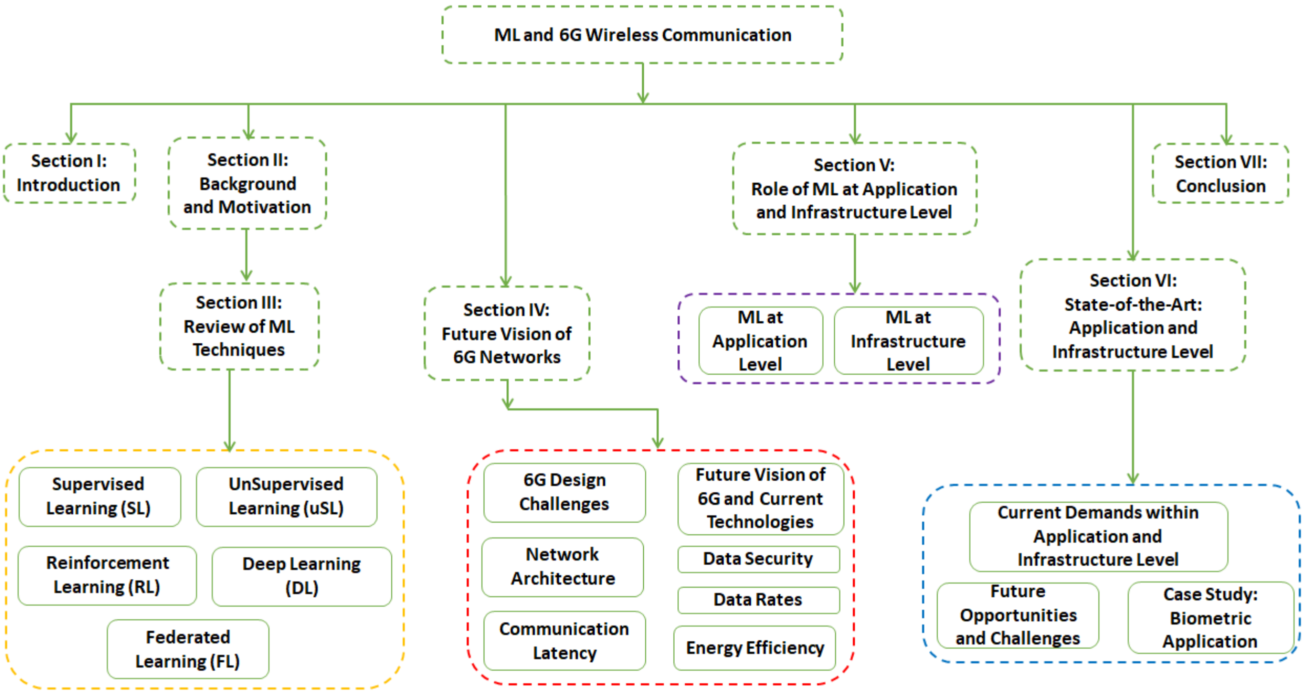

FIGURE 1. An overview of the topics covered in this paper.

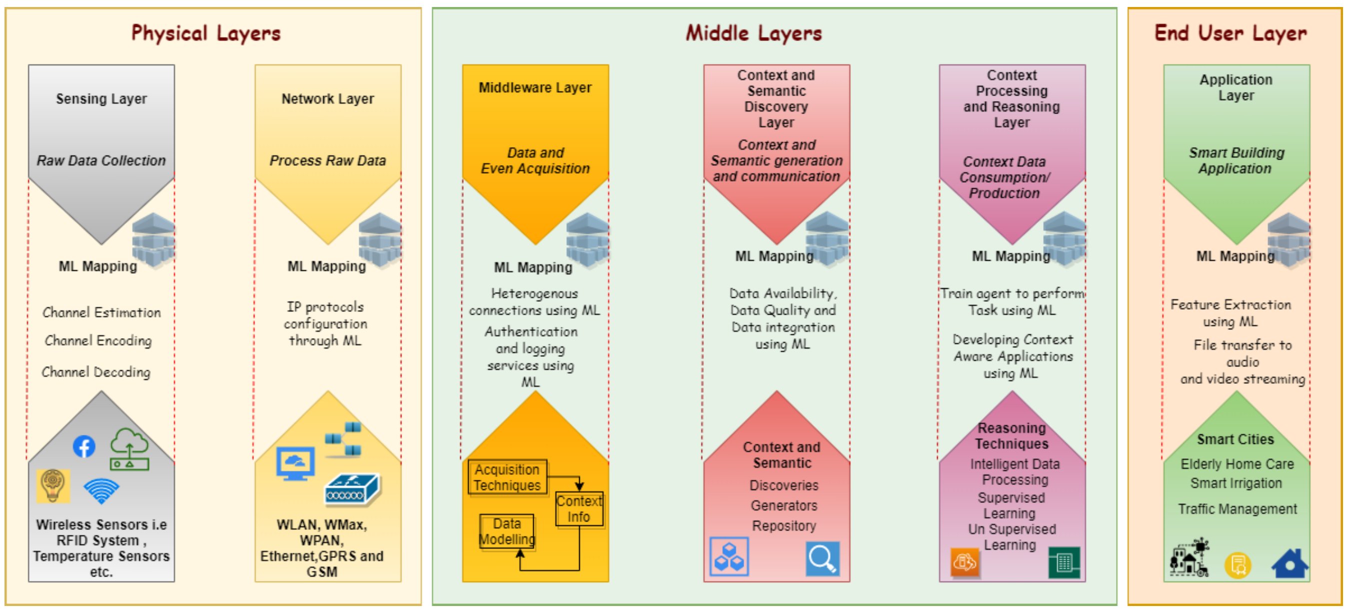

FIGURE 2. A conceptual representation of ML based 6G wireless network.

main component for the physical layer, transceiver design, network, and application layers. Although ML techniques are used for image processing and computer vision for a long time, the concept of using ML techniques for wireless communication is contemporary. The questions such as how ML techniques can be beneficial in wireless channel estimation and resource allocation and how ML techniques can be used to devise better network-layer protocols show the potential use of ML techniques for next-generation wireless systems. To address the questions mentioned above is the primary motivation for this article to review the role of various ML techniques for 5G and beyond wireless communication systems.

Another motivation of this article is to explore the question of how ML and AI will be embedded in various conventional layers of a wireless system, as shown in Figure 2. Generally, the conceptual OSI seven-layer model can be categorized into three main categories:

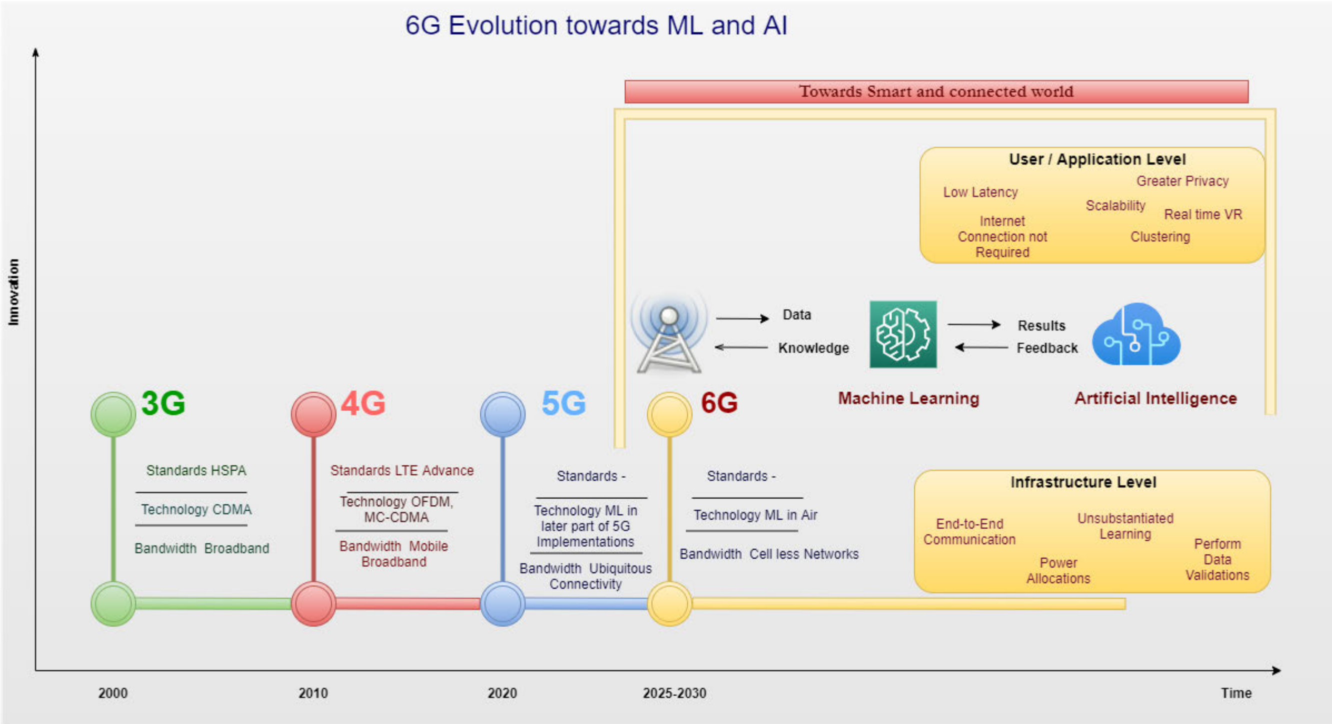

FIGURE 3. Evolution of 6G and potential role of ML techniques in this next generation wireless network.

- Physical layer (sensing layer, network layer)
- Middle layer (data link, network, transport, and session layers)
- Application layer

In future wireless systems, ML and AI will be embedded in all these layers and play a key role in system performance.

We have presented a conceptual layer model for 6G wireless system in Figure 2 and show the potential use of ML in each layer. To elaborate the Figure 2 further, it is shown how conventional wireless communication system resources can be integrated with ML. At different network levels, ML algorithms are to be trained with some given data sets and then deployed in mobile devices, base stations (BSs), core and management layer with network assistance (e.g., device programmability and configuration). These new techniques drive the need for a data-driven, and ML-native network as different network functions in the management domain require different sources of data.

In continuation of the above motivation, we have also focused on defining 6G evolution towards ML and AI, represented in Figure 3. Many existing researchers have concentrated on explaining the need of integrating ML with AI and how this integration has been applied in many smart areas for achieving improvement in people's lives, including the healthcare sector, business and entertainment, speech recognition, medical systems, and intelligent search engines [1].

The authors in [22] mentioned that today's era of technology represents tomorrow's reality such as pervasive connectivity, wellness applications, e-Health, and holographic telepresence in massive robotics and industry 4.0, smart environments, virtual reality, augmented reality, and tremendous mobility. Therefore, more efficient and effective wireless communication is required for each of these applications for enabling the massive exchange of data between heterogeneous devices, networks, and applications. Hence, 6G wireless networks must enable real-time, dynamic, fast, reliable, near-instant, and broadband wireless connections for data exchange at the various spectrum of frequencies by the use of different cutting edge technologies [23], [24].

The motivational aim of this article is to develop a baseline knowledge for ML techniques that can be used in wireless system design such as in channel modeling, channel estimation, transceiver design and for new user applications. The objective behind this concept is to design and build self-managed wireless networks that can utilise available resources efficiently and effectively without much human intervention. The ultimate goal is to provide better QoS to improve the human way of life.

III. REVIEW OF ML TECHNIQUES

Machine learning (ML) models are computational systems that are used to learn the discriminative features about a system that cannot be represented by a mathematical model. These models are commonly used in tasks such as regression, classification, and interactions between an intelligent agent and an environment. Once a model is trained on the given data, then this model can effectively takes the decision on unknown data and also performs the tasks based on arithmetic calculations. This will allows ML modeling for mobility, availability, accessibility, management of network communication based on 6G data, and improve and automate network performance management in order to keep current Key

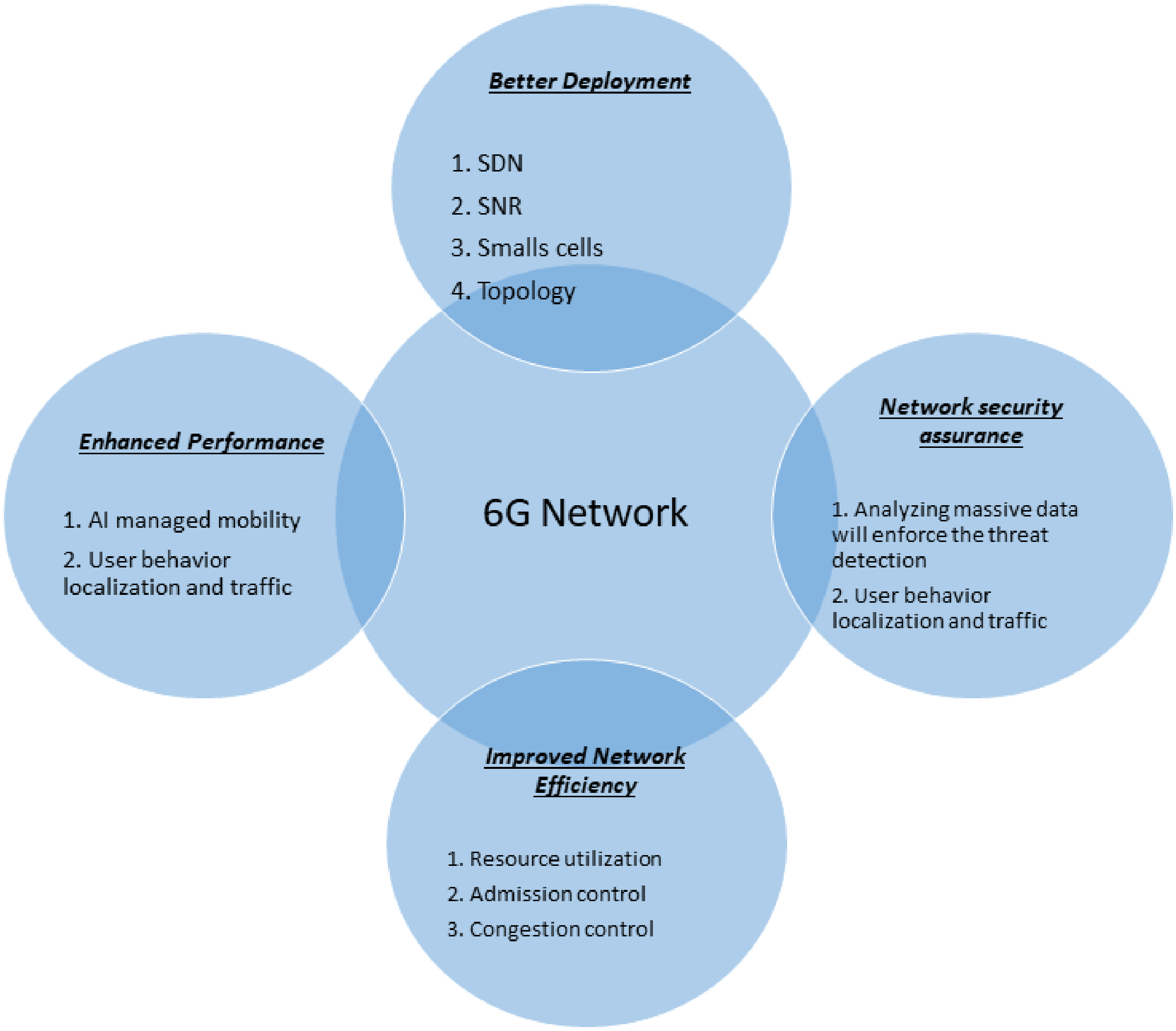

FIGURE 4. **6G network performance management using ML.**

Performance Indicators (KPIs) within predefined thresholds. ML also allows the management of 6G mobile networks with smart adaptive cells. This will improve beam management, power-saving, fault management, maintenance, operation, power control, network configuration, QoS prediction, throughput and performance of coverage. Figure 4 shows ML enhancing 6G network performance management aspects.

ML covers three paradigms which are known as a) supervised learning: where the learning of the model is to be carried out by using input samples and their corresponding outputs, b) unsupervised learning, in which the model learns to distinguish the input samples without any output labels and, and, c) reinforcement learning, where an agent communicates with an environment and learns to map any input to an action. An example of artificial neural network (ANN) operating at evolved parallel processing framework is illustrated in Figure 5 below.

ML is backbone of 6G wireless networks as it model the systems that can't be represented mathematically. Moreover, certain ML methods are already being used to substitute brute-force or heuristic algorithms to find optimal solutions for network problems. As ML makes its stride in 6G networks, it will be possible for real-time monitoring and automated zero contact operation and control. Moreover, ML predictions can be made by mobile devices and reported to the network for use in resource management, making mobile devices an integral part of the infrastructure. ML agents for 6G networks will be responsible for various roles including orchestration, network management, adaptive beam forming strategies and optimization of the radio interface. Such functionality involving data from various networks and domains. The role of ML in 6G networks is shown in Figure 6.

ML will play a key role in 5G and 6G wireless networks. As shown in Figure 2, every layer of the network will take advantage of ML techniques in one or other way. We envision that every traditional component of a wireless communication system will use ML techniques in their design. Therefore, it is important for wireless researchers to start thinking possible ways of integrating ML techniques in the wireless systems.

One of the key requirements of any ML model is the training data that is used to train the model in order to get the desired output from the model. Let us represent our generic

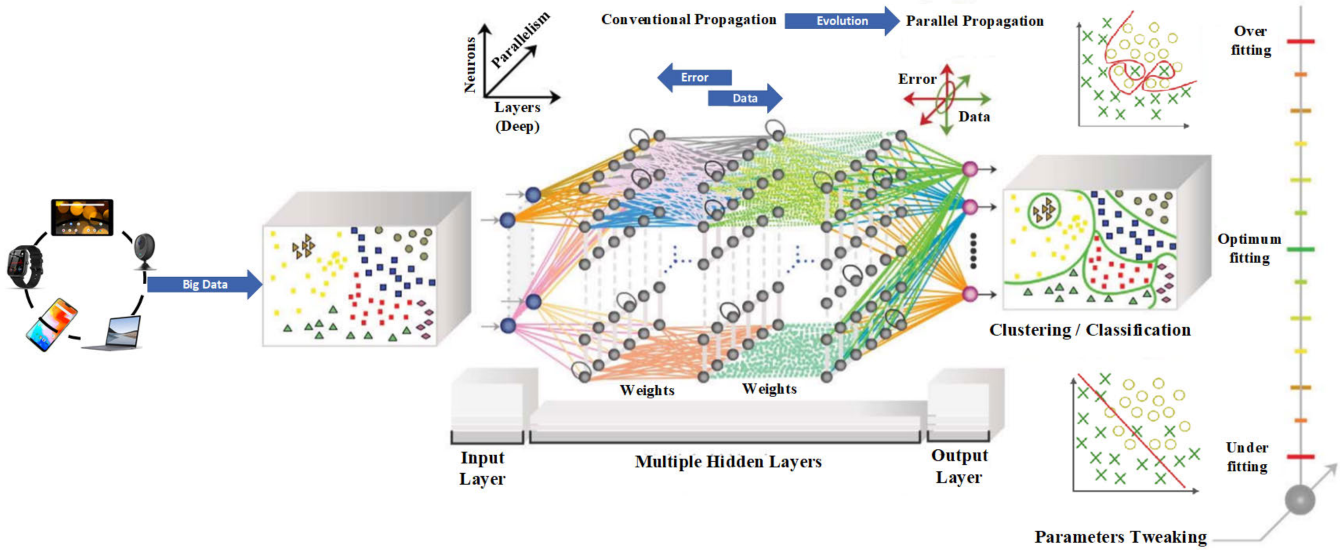

FIGURE 5. ANN Operating at Parallel Processing Framework in ML.

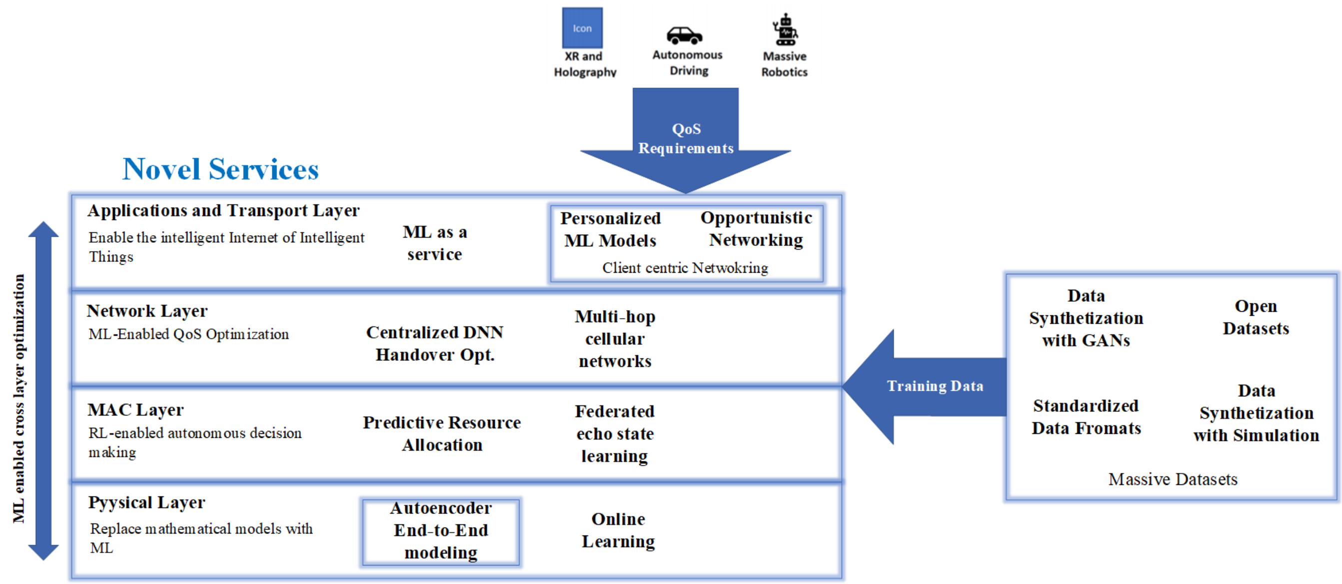

FIGURE 6. ML in 6G wireless network systems.

ML model by $\mathcal{M}$, training data set by $\mathcal{T}$, containing N training samples of some matrix $H \in \mathbb{C}^{(m\times n)}$ and the desired output by $\mathcal{O}$. Let us represent the input data set $\mathcal{T}$ as follows

$$\mathcal{T} = \{H_i\}_{i=1}^{N}, \tag{1}$$

where H_i represents an $(m \times n)$ dimension input matrix for the model $\mathcal{M}$. The desired output of $\mathcal{M}$ is $(m \times n)$ dimensional matrix, represented by $O \in \mathbb{C}^{(m\times n)}$. We can represent the overall ML process as

$$\mathcal{T} \longrightarrow \mathcal{M} \longrightarrow O. \tag{2}$$

An example of the application of such a model is to characterise the wireless channel for Ma-MIMO and mm-Wave applications. This channel estimation process through ML model $\mathcal{M}$ is also shown in Figure 7. Please note that this model $\mathcal{M}$ can use any of the ML techniques discussed in this section such as DL, FL, SL or uSL. The advantage of such a model is that the model $\mathcal{M}$ will reduce the wireless channel pilot feedback from users / devices through its learning model at the BS. This will reduce the bandwidth use for feedback channel and hardware reduction at the BS for the purpose of channel estimation.

FIGURE 7. An example of channel estimation using ML model $\mathcal{M}$ as given in equation 2.

In the following, we present a discussion on different ML techniques, their working principles, some advantages and

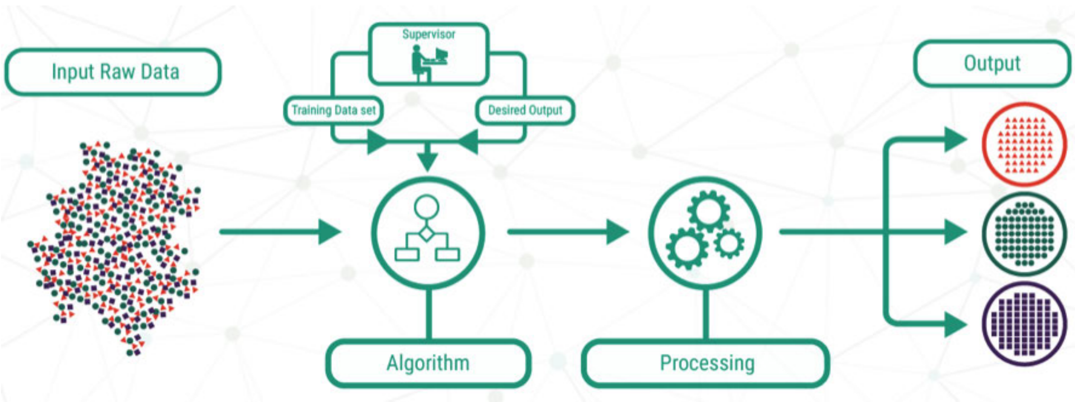

FIGURE 8. Supervised Learning.

limitations associated with them in the context of wireless communication systems.

A. SUPERVISED LEARNING (SL)

Introduction: Supervised learning (SL) is the ML method that uses labeled data sets $\mathcal{T}$ and performs a mapping of input function to output function as shown in Figure 9. On the basis of continuity of network, SL is classified into regression and classification. Some examples of the techniques for SL are Decision Trees (DTs), Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Support Vector Regression (SVR) and Gaussian Process Regression (DPR) algorithms.

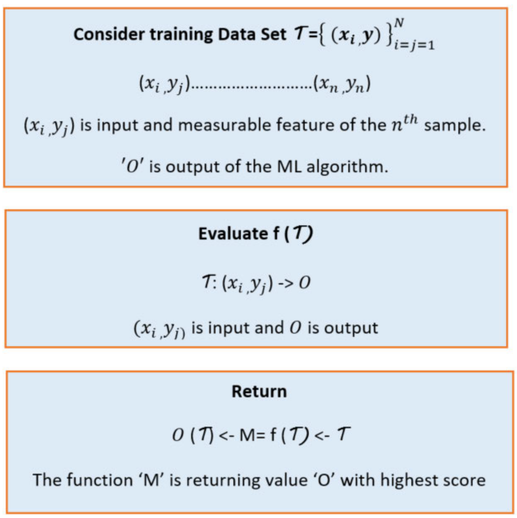

FIGURE 9. A flow diagram of the working of SL [25].

Working: The Figure 8 represents the process of supervised learning.

Advantages: SL techniques have a number of advantages in automation and decision making. Some key benefits of SL are listed below:

- SL focuses on solving real-world computational problems which includes predicting the numerical target values from given data sets.
- The output of SL can be generated based on previous experience where performance criteria can be optimized.
- SL is generally used in classifications and regression problems.

Limitations:

- Using SL unknown information cannot be retrieved from data sets.
- Accuracy of SL decreases in case of large data sets.
- In SL clustering and classification of data sets cannot be performed by discovering features by itself.

B. UN-SUPERVISED LEARNING (uSL)

Introduction: Unsupervised ML (uSL) uses unlabeled data sets to learn the functions that can be used for describing hidden data patterns and structure. The techniques for unsupervised ML are K-means clustering, hierarchical clustering algorithms, Principal Component Analysis (PCA), and ISOmetric MAPping (ISOMAP). The Figure 10 represents the process of unsupervised learning.

Working: The input for unsupervised learning is data set $\mathcal{T}$. $f(\mathcal{T})$ is a model, (x_i, y_j) is input data and O is output of ML algorithm. This explanation of uSL can be written mathematically as [26]:

$$f(\mathcal{T}) = \mathcal{M}, \tag{3}$$

$$constant = a \quad \text{(Starting point)}, \tag{4}$$

$$\text{Expected Output} = E\Big[\big(O - f(\mathcal{T})\big)^2\Big], \tag{5}$$

where $f(\mathcal{T})$ is the functional definition of model $\mathcal{M}$, a is a constant representing a starting point of the algorithm, E is the expectation operator and 'Expected Output' represents the cost function calculated using equation (5). Therefore, if the Expected Output is minimised, then value of a is statistical mean of the input data set $\mathcal{T}$.

Advantages:

- uSL is less complex as it does not require the labeling of data.
- It functions in real-time as all the input data sets are labeled and analyzed by users at the beginning of the algorithm.
- It is widely used for cluster analysis to track the hidden patterns.

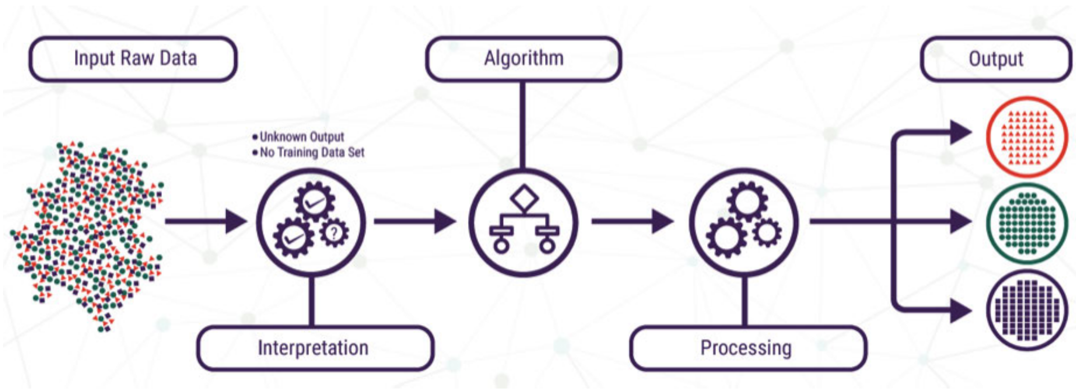

FIGURE 10. An example of Un-supervised ML model.

FIGURE 11. An example of Reinforcement Learning ML model.

Limitations:

- Labelling of data sets is required before identifying the hidden patterns.
- It is less accurate as compared to other ML techniques as input data is not labeled.
- Unsupervised learning is computationally complex.

C. REINFORCEMENT LEARNING (RL)

Introduction: Reinforcement learning focuses on making suitable decisions that are generated by mapping the situations to actions and evaluating which actions have to be considered for maximizing a long-term reward. The techniques for Reinforcement learning are Markov decision process (MDP), Q-Learning, policy learning, actor critic (AC) and multi-armed bandit (MRB).The Figure 11 represents the process of reinforcement learning.

Working: In RL algorithm, policy is identified by mapping set of states to the set of user actions. Once the probability of policy is identified, the state value function is used for calculating expected return R[R]. Finally, return(R) is estimated as shown in Figure 12.

Advantages:

- RL can handle delayed rewards, partial observations, and stochastic decision making.
- The changes to data sets can be sustained for a longer period.

Evaluate Policy : Probability of taking action 'a' in state 's' for selection of agents in modeled as follows

Π: A X S -> [0, 1]

$$\Pi\ (a, s) = \Pr\ (a_t = a \mid s_t = s\ )$$

State Value Function: Then algorithm calculates value function v_π for estimating maximum reward in given state's'

$$v_\pi(s) = E[R] = E\ \sum_{r=0}^{\infty} \gamma^T r_t | s_0 = s$$

R is return Value

Return: Then algorithm calculates 'R', which is, return variable calculated as

$$R = \sum_{r=0}^{\infty} \gamma^T r_t$$

r_t is reward at step t, $\gamma^T r_t$ is discount rate

FIGURE 12. A flow diagram of the working of RL [27].

- RL can be used in a vast environment where simulation-based optimization is needed.

Limitations:

- Much usage of RL can diminish the results because of the overloading of states.
- RL only addresses the expectancy level of minimum behavior.

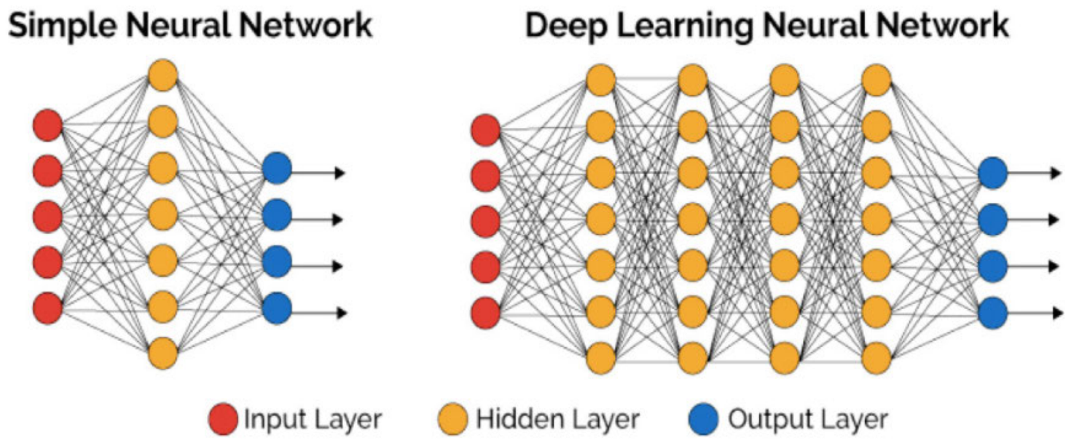

FIGURE 13. An example of Deep Learning ML model.

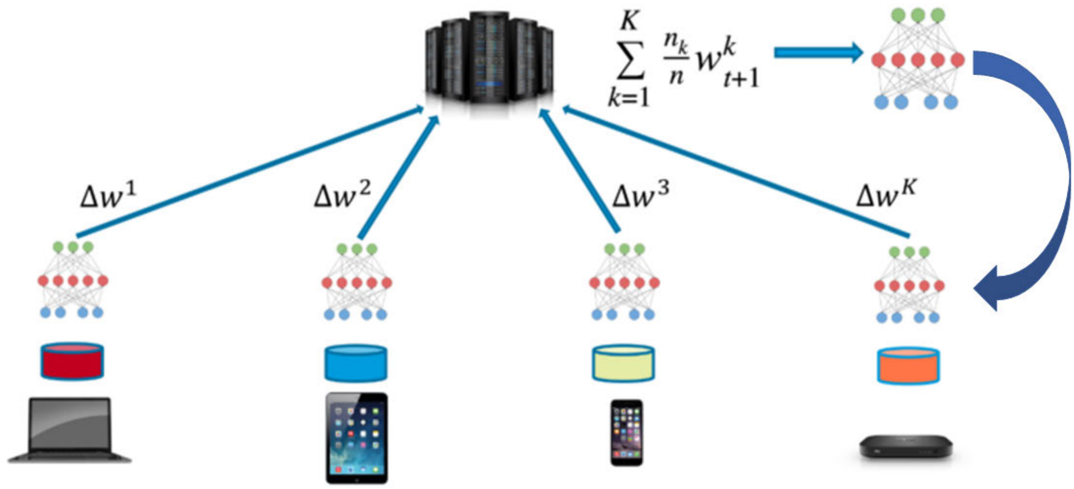

FIGURE 14. An example of Federated Learning.

D. DEEP LEARNING (DL)

Introduction: Deep learning is a function of AI that understands the function of human brains and use that understanding to create patterns based on artificial neural networks that contain neurons in multiple layers. Some of the common techniques used for DL are Deep Neural Network (DNN), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM) and Convolutional Neural Network (CNN).

Working: Figure 13 shows the conceptual working process of DL where hidden layers carry out the iterative method. The initial level focuses on simple information that machines can learn, and with an increase in levels, information keeps on constructing. On each increase the new information is combined with previous information and final out is combined information of inputs.

Advantages:

- Using DL more learning models can be created by adding more layers to the existing neural network. This enables high dimensionality.
- The training process in DL is less complex as it handles data sets at a higher level of abstraction.
- Computational power is not affected by DL.

Limitations:

- DL requires a large amount of memory and computational resources for processing.
- Very advanced optimization techniques are required by DL, thereby making it more costly and complex.
- Large data sets are required by DL making it more difficult to understand and implement. It also affects the accuracy of output.

E. FEDERATED LEARNING (FL)

Introduction: FL is the collaborative learning which trains and updates the algorithm through the joint effort of multiple servers or edge devices that are deployed in decentralized manner within the network. FL does not exchange the local data samples across the edge devices, instead it shares the model with the other participating servers or devices. The Figure 14 shows the process of federated learning (FL).

Working: FL based techniques focus on federations of clients that take significant amount of task for the optimisation of the main model, however, there is one central server that coordinates everything with the participating nodes or devices [25], [28]. Before server commences distributed learning process, the learning model $\mathcal{M}$ is initialized with the default values, which we call as $\mathcal{M}_0$. After initialization of model $\mathcal{M}_0$, the iterative training and updating process of the model $\mathcal{M}$ begins. As an example, let us consider there are D devices in the network and the main server selects S devices from total D available devices to participate in the update of the model $\mathcal{M}$. Let us represent the set of devices D and S as follows

$$\mathcal{D} = \{d_1, d_2, \cdots, d_D\} = \{D\}_{i=1}^{D}, \tag{6}$$

and

$$\mathcal{S} = \{s_1, s_2, \cdots, s_S\} = \{S\}_{i=1}^{S}, \quad \text{s.t. } \mathcal{S} \subseteq \mathcal{D}. \tag{7}$$

During this process the server selects S devices randomly which estimate the required parameters locally for the optimisation of model $\mathcal{M}$. Once they achieve the required estimation, these devices sent back their information to the main server. The main server then aggregates all the information from S participating devices to use for achieving an overall optimised model $\mathcal{M}_f$ where subscript f is representing the final stage of the model for that particular iteration. Let us assume that the parameter that each device needs to estimate is its wireless channel represented by $h(s)$ where s represents the relation of h with its particular device s. We further assume $\hat{h}$ as the estimate of h. Then we can represent the FL based model update or training process as

$$\mathcal{M}_f \longleftarrow \mathcal{M}_0 + \sum_{i=1}^{|\mathcal{S}|} \left(\hat{h}_i\right), \tag{8}$$

where $\mathcal{M}_f$ represents the final FL based model achieved at the main server at the end of one iteration. This process continues, until all the parameters of the global optimised model $\mathcal{M}$ are converged according to a predefined criteria.

Advantages:

- FL provides more data security and privacy as all the training is performed on devices directly.
- FL uses minimal hardware for processing. This decreases the cost of processing associated with it.
- It does not require connectivity while working as models are directly installed on devices.

Limitations:

- FL uses multiple devices for centralization and decentralization, thereby leading to connectivity issues among the devices.
- Difficult to develop an infrastructure for continuous learning.
- As millions of devices are connected for communication, which makes FL more expensive as compared to other ML techniques.

IV. FUTURE VISION OF 6G NETWORK

This section describes the performance metrics with 6G expectations and what are possible design challenges within these metrics. Further, this section focuses on two areas

- 6G expectations and design challenges are shown in Table 1.
- Future vision of 6G and related technologies are shown in Figure 15.

A. 6G DESIGN CHALLENGES

There are many innovations in the field of wireless technology, but their innovations have raised few performance requirements [14], [31]. Table 1 elaborates some of the challenges for beyond 5G network and how they can be addressed by technologies which can be a step moving towards 6G communication networks. The performance metrics such as peak throughput, higher energy efficiency, connection everywhere and anytime, new theories and technologies, self-aggregating communications fabric are considered and mapped for the expectations of 6G.

B. FUTURE VISION OF 6G AND CURRENT TECHNOLOGIES

The need for next-generation mobile communication systems is arising due to the scalable deployment of 5G wireless networks. Many pieces of research [32] are focusing on the future of 5G that leads to 6G. The authors future vision of 6G with disruptive techniques, cell-less networks, intelligent connectivity, seamless coverage, distributed antenna system, is shown in Figure 15. To satisfy the needs of future 6G, the below potential key technologies can be used:

Holographic Radio: The authors in [33] mention that the efficiency of spatial multiplexing can significantly be improved using holographic radios. Some of the characteristics of holographic radios are ultra-high coherence, high spatial multiplexing, infinite multiplexing space, and space-correlation propagation model.

Massive Multiple-Input Multiple-Output (Ma-MIMO): The the main aim of Ma-MIMO is to become excellent PHY layer technology for 5G and 6G by providing better throughput and efficiency by using the available spectrum efficiently. In Ma-MIMO, the number of transmit antennas at BS are large compared to conventional MIMO systems, i.e. ($N_t \longrightarrow$ in the order of hundreds), and therefore Ma-MIMO can have the potential to support the modern applications promised by new wireless technologies by exploiting spatial dimensions of the system. However, it is still an active area of research that whether Ma-MIMO can work seamlessly for 6G or another new PHY layer technology would be needed.

Tera Hertz (THz) Communications: The authors in [33] mentioned that THz is used to provide high data speed to meet the demands of increasing throughput and to achieve low latency for wireless 6G networks. The advantages of THz are spatial resolution achieved through higher frequency, high-precision positioning, huge bandwidth to support the Tbps links [7], [15].

V. ROLE OF ML AT APPLICATION AND INFRASTRUCTURE LEVELS

This section describes the role of ML techniques at application and infrastructure level in terms of power allocations,

TABLE 1. 6G performance metrics, technology expectations and some research design challenges.

Performance Metric	6G Expectations	Design Challenges
Network Architecture	The growing capacity, frequency demands due to the rise of smart cities cannot be addressed through static base stations (BSs).	1) This issue can be resolved by hybrid cellular networks such as mobile base stations (BSS) using Hybrid cellular networks [5]. 2) In order to meet the increasing demand of resources in communication networks the mmWave technology plays an important role. With the use of the coverage area between satellite and terrestrial communication networks is increased [7]. 3) Efficient spectrum sharing and route optimization for the UAV parameters can be achieved by ML tools with the use of mobile base station (BSS) and dynamic spectrum sharing [1], [7].
Data Rates	In order of magnitude there is huge increase in targets of wireless communication networks.	1) Free spectrum is available in the Tera Hertz (THz) frequency band in 6G. 2) 6G have high bit-rate short-range communications. 3) 6G supports high bit rates in range of the millimeter waves band between 100 GHz and 300 GHz [3]. 4) The high data rates can be supported using light-emitting diodes (LEDs) as transmitters and photo diodes as receivers .
Energy efficient	Due to increase in no of devices with the advancement of smart cities the wireless communication networks are facing difficulties with network deployment and resource allocation.	1) Using smart surfaces consisting of re-configurable planar meta-materials will help in the reduction of interference when they are implied with electromagnetic waves. These meta materials provide adsorptions of radiations and beam-steering for signal-to-noise ratio(SNR) maximization [21]. 2) Another possible solution is using energy efficient approach for deployment of network and allocation of resources. It includes technologies such as M-MIMO and ultra-dense heterogeneous networks [1].
Data Security	Large Quantity of data is stored on mobile networks in forms of text massages and Geo-tagged voice. It is one of the biggest challenges of ML.	1) Security schemes of physical layers should be deployed with conventional cryptography schemes [29]. 2) Using ML-based schemes (as discussed in Section III) for protections against cyber attacks [29], [30] . 3) Deployment of security within physical layer should be clubbed with conventional cryptography schemes. Also, ML-based schemes for cyber security and quantum encryption [15] are promising approaches to be explored for securing communication links in future 6G networks.
Latency	Viewing experiences issues by non-synchronized video and audio, bad user interface.	1) Using a bionic system that is integrated with neural motors that help the neural network to function directly on the device with fast speed and low latency. 2) Including the existing features that are already preloaded in ML kits . 3) Graphic processing unit (GPU) helps the applications for faster processing of data probably at the speed of light, thereby reducing and eliminating the errors from applications.

caching, load balancing, and clustering. The main aim of this section is to elaborate on how ML and 6G can be used more productively to benefit users and help 6G networks to meet the future challenges and user expectations from these networks.

A. ML AT APPLICATION LEVEL

At the application level, ML uses powerful functions in terms of using the location of users to provide sensitive information, performing face recognition, etc. which have provided revolutionary changes for meeting the rising demands of low latency and faster processing [19]. Application layer act as the interface between the user and smart applications where the main aim of the application layer is the effective management of resources, automation of tasks, and improvement of security and safety through ubiquitous and continuous monitoring. To achieve the above performance metrics application is directly installed on smartphones that use built-in deep learning algorithms or using actuators that control the living environment of residents [17]. The main contributions of ML techniques at application level are:

- **Power allocation**: ML at the application level uses supervised learning for intelligent caching and contents prediction. The example is satellite links used for coverage of the global network. These links are used for enabling low latency communication in remote regions [34]. Secondly, ML determines the user association with base stations (BSs) through content demands and using techniques such as neural networks and radio access networks (CRAN) to predict the contents and mobility patterns there focusing on power allocation among the 6G wireless resources.
- **Clustering:** With the use of supervised and unsupervised learning at higher layers can perform grouping/ clustering of nodes/points for optimal allocation of

FIGURE 15. A future vision of 6G wireless technology.

network resources [34], [35]. Moreover, various potential applications for data analysis through clustering are trends in social networking analysis at the network side, phone-apps data analysis at user and networks, and ranking of web resources.

- **Learning requirements and capability:** Real-time data processing applications requirements do not fit with current batch processing ML algorithms [14]. Online training is a suitable solution for such streaming data applications. However, in online training, only a limited fixed time is available for processing each data sample. A typical application of offline (batch) and online learning in communication systems can be intelligent caching and channel tracking. Reinforcement learning at the user level usually optimizes the performance indexes through available objectives functions with high computational efficiency [10], [15].
- **Load Balancing:** Most of the previous ML algorithms often assume static channel quality, which is not feasible in the real world [36]. Adopting ML based on the base station (BS) at the application level will build association among small cell base stations (SBSs) and medium cell base stations (MBSs) and meet the current demands of load balancing in 6G network. Also, the use of SBSs reduces the cost of network operations.

B. ML AT INFRASTRUCTURE LEVEL

At the infrastructure level, ML has begun to penetrate the field of wireless communication. The infrastructure level of traditional wireless communication is generally designed based on client-server interactions, mathematical models, where several major modules are modeled and optimized separately.

The main contributions of ML techniques at infrastructure level are:

- **Power allocation:** At infrastructure level, supervised ML is where true joint distribution of output and input parameters in client-server architecture. In infrastructure level, ML uses the multiple nodes for power allocation where the load is distributed across entire network. But, there can be situations where infrastructure level where power distribution within the network is not known e.g. for in case body area network (BANs) at infrastructure level, accurate model of propagation channel is not

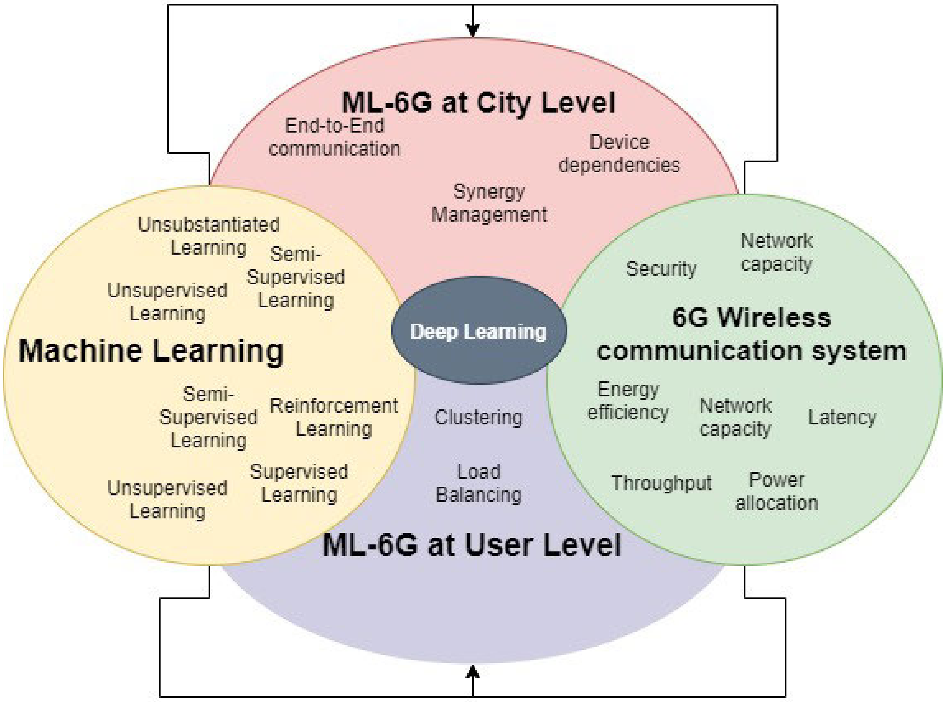

FIGURE 16. ML techniques for 6G at application and infrastructure levels.

available [37] which affects the power allocation among entire network.

- **Training system:** In the area of semi-supervised learning, annotated training data in small amount is available with most of the unlabeled data but in the area of unsupervised learning, no such data is available. In unsupervised learning, the collection of available input data samples are exploited to train the system without any systems prior information [19], [34]. For example, noisy data symbols at the physical layer are used to train system by sample points clustering for generation of effective nonlinear decision boundaries in order to map symbols as per constellation maps. Both unsupervised and semi supervised learning are used for classification and clustering. The learning methods implementation structures can be named as: maximum likelihood learning, Principal Component Analysis (PCA), k-means clustering etc.
- **Unsubstantiated learning:** Unsupervised learning is applied for various kinds of tasks for example, clustering, sample generation, distribution specific and features classification. However, at infrastructure level, when there are high dynamic scenarios, the coherence is less which further limits the availability of data and time required for supervising clients and servers [5]. Furthermore, using ML at infrastructure level will enable the tracking operation and channel equalization through unsupervised and semi-supervised learning. Unsubstantiated learning at this level also helps to achieve performance optimization and precoding/encoding schemes selection.
- **Learning requirements and capability:** ML algorithm model can be determined on the basis of nature and amount of data in progression. Batch-learning algorithms can be used at infrastructure level for applications where large amount of prior data is available. These algorithms search space for every possible structure of knowledge with the unlimited time of computing. These kinds of methods where data is obtained manually, batch-processed and labelled is having a constraint of limited data.

VI. STATE-OF-THE-ART: APPLICATION AND INFRASTRUCTURE LEVEL

This sections focuses on identifying the common areas between ML/6G at application and infrastructure level as shown in Figure 16. Further, this section is divided into two levels as shown below:

- Identifying best fit for current demands at application and infrastructure level as shown in Table 2.
- Case study: Understanding biometric application from both perspectives.

A. CURRENT DEMANDS WITHIN APPLICATION AND INFRASTRUCTURE LEVEL

This section focuses on analysing current demands of wireless communication system and smart applications and identifying where these demands fit from prospective of user

TABLE 2. User vs infrastructure level - An overview of future 6G applications.

Current demands	Application level	Infrastructure level	Reasons
Low latency	✓	×	1) High E2E latency in applications leads to numerous problems, e.g. bad user experience and loss of customers. 6G based applications will require latency as low as close to real time processing. 2) The major manufacturer of smartphones, Apple uses low latency concept for their mobile apps. For examples, their Bionic system integrated with neural motors helps neural network for functioning on the device with low latency. Also, preloaded features are added by google to the ML platform kit and Tensor flow lite [38]. 3) The manufacturers develop apps with the help of these technologies to process the data at faster speeds, eliminating latency and reducing errors.
Large scale data breaches	✓	×	1) More chances of data breach at central location
Perimeter defence	×	✓	1) Perimeter is easier to define due to central storage and location
Internet connection not required	✓	×	1) With the usage of ML on various applications, there is the implementation of neural networks in mobile that allow developers for implementing the device technology without an internet connection at any time. 2) In a health-care industry, where there is the usage of ML on devices, where tools are created by developers for verifying the signs without an internet connection.
Greater security and privacy	✓	×	1) More security of data using ML at user level as data is not sent to cloud or servers for processing. 2) Using edge computing on mobiles, allow block chain mechanisms to be decentralised. [10], [14], [19].
Scalability	✓	×	1) Storage and data processing is distributed across various devices instead of storing at one central location.
Device dependence	×	✓	1) Size of mobile applications is reduced, requiring less storage space on devices.
End-to-End (E2E) communications	×	✓	1) With the use of deep learning the significant performance improvements are seen in case of E2E communication where the principal behind the design is to decompose signals into multiple independent blocks along the chain [17]. This helps the communications at the city infrastructure level to be efficient, versatile and controllable.
Synergy management	×	✓	1) Between the various applications designed for various objectives proves more difficult magnitude orders then the development of each application. 2) Also open research question is the social aspects of the application and technical challenges. Various examples include compliance and social acceptance with existing safety and security regulations.
Reduced costs for businesses	✓	×	1) On the usage of the smartphone of ML enables the cost-saving in organizations that are paid for storage to external providers or internet payment as sophisticated NPU (Neural Processing Units) present in smartphones. 2) Also the data processing between mobile and cloud involves cost that has to be be paid by an organisation [23]. Hence choosing AI or ML on device will cut organisation cost.Additionally,this leads to reduction of bandwidth that saves cost.
Performing data validations	✓	✓	1) The enrolled data sets are validated and supervised through identify the proofing process. For example, in the case of biometric at server-centric, the validation is performed through the proofing process where identification of preloaded data set is done at a central location.

and infrastructure level as shown in Table 2. For example, low latency is more likely to occur at user level due to emergence of AI and 6G wireless communication whereas perimeter defence is more likely at infrastructure level where communication is between client and server.

To briefly describe the futuristic applications of 5G and beyond, which employ ML techniques, let us consider the future researchers develop the real-time VR 6G application in the tourism industry. With this application, tourists will be provided with VR glasses, which will guide them to have a virtual tour of the whole site they want to visit and explore. Meeting the demands at the application and infrastructure level through 6G and ML indicates the future direction for this intelligent 6G - ML application. Another example can be consider, where we can measure global spread of COVID-19 through building AR-VI application. This application will use AI-ML to integrate the data from three source: travel, population and disease data to measure how fast the disease can spread and how it can be intervene at early stages.

B. CASE STUDY: BIOMETRIC APPLICATION AT APPLICATION AND INFRASTRUCTURE LEVEL

1) ML/AI SERVER CENTRIC

The template for biometric application is stored in sever at central location where the matching and liveness detection are performed at a central location on the server-side. Each time verification attempt is sent, it goes to the central matching engine where the entire processing against the template is stored centrally on the server [37]. The main issue with server-centric is security and networking due to which the demand from client-server applications is decreasing among the large sectors such as healthcare and finance.

2) ML/AI USER CENTRIC

In this level of AI, all the process occurs locally where the creation of template, storage and matching of biometric template is done on device itself [37]. In fast identify online system (FIDO), access to private key is granted which is stored in device. In case of upcoming surge of smart cities, many organisational sectors such as healthcare, finance are preferring ‘‘one-size fits all’’ model with the increase in volumes of data set. There are genuine concerns that organizations operating in highly regulated sectors, such as finance and healthcare, can trust a ‘‘one-size fits all’’ model. With this model, the capture and storage of biometric identity data are managed by a hardware OEM using algorithms tuned to be more convenient than secure.

C. OPPORTUNITIES AND CHALLENGES’

This section focuses on describing future challenges and opportunities that networks can have while employing machine learning in 5G and beyond communication as discussed below:

1) RESOURCE ALLOCATION USING ML

Resource allocation in IoT systems using ML techniques is progressively turning into complex problem [39]. Due to massive advancement in usage of wireless devices and increase in system uncertainties(e.g., dynamic variations in channel and traffic, multi-dimensional Quality of service (QoS) requirements), there is upsurge in optimization problems within the resource allocations. Although, there are many existing solvable solutions that focus on resource allocation by simplifying the problems through relaxing constraints. However, to reduce the current complexity for allocating resources using ML, new processes or methods will be required.

2) MANIFOLDNESS USING ML

The huge shift in IoT networks has increase the amount of multidimensional data [30], [39]. Currently, ML techniques are performs specific functions. However, usability of data in IoT networks depends upon the application domain. Therefore, ML algorithms need to be investigated further for handling the data in intelligent manner.

3) POWER ALLOCATION USING ML

Due to large scale IoT network, there is increase in intracell and intercell interference issues [40]. Many smart applications are heterogeneous and use varied channel and network topology. Therefore, it is challenging to choose ML techniques with 6G that can transmit power dynamically with response to network parameters and varied physical channel. This further need an investigation.

4) DATA REDUCTION USING ML

The existing ML algorithms are able to identify the analytical regularities in large data sets, but are short of efficacy and external validity when they are associate at application level. More research needs to be done on developing an integration framework for various applications using ML and 6G wireless communication. Further, investigating on how the training data reduction method can be deployed at higher level layers to develop an fully autonomous system

5) WIRELESS CHANNEL MODELING USING ML

Currently ML techniques are used for handling big data however, designing of future wireless communication system will require large amount of channel data and appropriate channel models that should be based on statistical methods. Currently, in wireless communications, high bandwidth transmission is enabled through channel modelling. However, with emerging 6G and IoT, the need for efficient channel allocation and channel modelling is increasing that is leading to another future direction.

VII. CONCLUSION

In this article, we have discussed various ML techniques and their working. Furthermore, we have also covered the accepts of 6G communication system along with its challenges and future vision. Followed by 6G future vision we have elaborated how ML at application level and infrastructure level can be more productive to meet the future 6G challenges. The state-of-the-art is discussed where the current demand of 6G are analysed and compared. It is evaluated that application level is best fit for filling the gaps of 6G challenges as compared to infrastructure level. Followed by best fit, the case study-biometric application has been discussed. The case study shows how smart biometric application works at application level and infrastructure level. To this end, we have identified the future directions in using ML in resource management, power allocations, data reductions and channel modelling. There are many ML techniques that can been run intelligently when combined with 6G wireless communication network. Therefore, for current ML and future 6G, we need to build a solution for meeting the current challenges such as latency, power allocation, privacy, security, inter-operate ability of models, etc. at application level and infrastructure level to enhance the smart applications.

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JASNEET KAUR (Member, IEEE) received the bachelor's degree in computer science from Punjab Technical University, India, the master's degree in computer science from GNDEC, India, and the master's degree (Hons.) in information technology specialization in networking from Charles Sturt University, Australia, where she is currently pursuing the Ph.D. degree. Her research interest includes design and developing ML techniques for wireless channel estimation, including massive MIMO and millimeter wave (mm-Wave) channels for 5G and beyond. Her research is applied to smart applications and future wireless communications, such as 5G and 6G. She is a member of the Australian Computer Society (ACS). She received the Dean's Award for her master's degree with Charles Sturt University.

M. ARIF KHAN (Member, IEEE) received the B.Sc. degree in electrical engineering from the University of Engineering and Technology Lahore, Pakistan, the M.S. degree in electronic engineering from the GIK Institute of Engineering Sciences and Technology, Pakistan, and the Ph.D. degree in electronic engineering from Macquarie University, Sydney, Australia. He is currently a Senior Lecturer with the School of Computing and Mathematics, Charles Sturt University, Australia. His broad research interests include future wireless communication technologies, machine learning for wireless communication, massive MIMO based wireless systems, and cyber security. He was a recipient of the prestigious International Macquarie University Research Scholarship (iMURS) and the ICT CSIRO Scholarship for his Ph.D. degree. He also has the competitive GIK Scholarship for his master's degree.

MOHSIN IFTIKHAR (Member, IEEE) received the B.Sc. degree in electrical engineering from the University of Engineering and Technology Lahore, Pakistan, the M.Eng.Sc. degree in telecommunications from UNSW Sydney, Australia, and the Ph.D. degree from the University of Sydney, Australia, in 1999, 2001, and 2008, respectively.

He was a Consultant with National Information, Communication and Technology Australia (NICTA) and Soul Communications Australia, from 2007 to 2009. Further, he used to train Ericsson Australia employees on different Cisco networking products. He had been working as an Associate Professor with the Department of Computer Science, King Saud University, Riyadh, Saudi Arabia. He had been also affiliated with NICTA (www.nicta.com.au) as a Visiting Research Fellow and an Honorary Research Associate with the School of Information Technologies, University of Sydney (www.it.usyd.edu.au). He is currently working as a Senior Lecturer with the School of Computing and Mathematics, Charles Sturt University, Australia. Additionally, he had been working as an Honorary Visiting Fellow with the School of Engineering and Mathematics, La Trobe University, Melbourne, VIC, Australia. His research interests include the IoT, software defined networks (SDN), machine to machine (M2M) communication, Quality of Service (QoS), traffic modeling, polling models, 3G/4G networks, Markov chains, stochastic processes, WiMAX network, and network calculus.

Dr. Iftikhar is a member of ACM and IET, and PMI and ISACA.

MUHAMMAD IMRAN (Member, IEEE) received the Ph.D. degree in information technology from University Teknologi PETRONAS, Malaysia, in 2011. He is currently an Associate Professor with the College of Applied Computer Science, King Saud University, Saudi Arabia. His research is financially supported by several grants. He has completed a number of international collaborative research projects with reputable universities. He has published more than 250 research articles in peer-reviewed journals and well-recognized international conferences and journals. His research interests include the Internet of Things, mobile and wireless networks, big data analytics, cloud computing, and information security. Many of his research articles are among the highly cited and most downloaded. He has been consecutively awarded with the Outstanding Associate Editor of IEEE Access, in 2018 and 2019, besides many others. He has been involved in about one hundred peer-reviewed international conferences and workshops in various capacities, such as the Chair, a Co-Chair, and a Technical Program Committee Member. He is serving as an Associate Editor for top ranked international journals, such as *IEEE Communications Magazine*, IEEE Network, *Future Generation Computer Systems*, and IEEE Access. He served/serving as a Guest Editor for about two dozen Special Issues in journals, such as *IEEE Communications Magazine*, *IEEE Wireless Communications Magazine*, *Future Generation Computer Systems*, IEEE Access, and *Computer Networks*. He served as the Editor-in-Chief for the European Alliance for Innovation (EAI) Transactions on Pervasive Health and Technology.

QAZI EMAD UL HAQ received the M.S. degree from the National University of Sciences and Technology (NUST), Islamabad, Pakistan, and the Ph.D. degree in machine learning from King Saud University, Riyadh, Saudi Arabia. His research interests include security analytics, the IoT, network security, machine learning for 5G and beyond, artificial intelligence, pattern recognition, deep learning, medical image, and signal processing.