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# A MACHINE LEARNING APPROACH IN COMMUNICATION 5G-6G NETWORK

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**ABSTRACT**

Applications in the fields of entertainment, commerce, health, and public safety rely heavily on wireless communication technologies. These technologies are constantly improving with each new generation, and the latest example of this is the widespread implementation of 5G wireless networks. Industry and academia are already planning the next generation of wireless technologies, 6G, which will be an improvement over 5G. When it comes to 6G systems, one of the most important things is that these wireless networks employ AI and ML. There will be some kind of artificial intelligence or machine learning used in every part of a wireless system that we know about from our experience with wireless technologies up to 5G, including the physical, network, and application levels. A current overview of concepts for future wireless networks, including 6G, and the relevance of ML approaches in these systems is presented in this overview article. Specifically, we set out a 6G conceptual model and demonstrate how ML approaches are utilized and contribute to each layer of the model. With wireless communication systems in mind, we take a look back at many ML methods, both old and new, including supervised and unsupervised learning, RL, DL, and FL. At the end of the article, we touch on some potential future uses and difficulties with 6G network ML and AI research.

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

## 1. INTRODUCTION

A large number of researchers and academics are now working on Sixth Generation (6G), a novel wireless technology. The primary goals of 6G are to expand the advantages of artificial intelligence and machine learning in wireless networks and for consumers. With the help of AI and ML, 6G will also provide improvements to technical metrics like throughput, the ability to support new apps with high demand, and the efficient use of radio frequency bands, among many other things [1]–[3]. With its many uses in learning from more human-like circumstances, DL is one of the main ML technologies expected to play a pivotal role in 6G. For 6G, DL may determine which access point to use and which resource controller has more available resources.

Interestingly, deep learning has been showing promising results when used to classification issues, although the exact function of DL in wireless networks remains a mystery. Nevertheless, this article offers a general outline of ML methods, including DL, and their possible

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function in upcoming 6G communication networks. There are more and more real-world uses for wireless technology, and it is constantly developing and improving to meet the demands of its users [4]. The 5G mobile communication system improves localization accuracy, increases data speeds, and decreases energy consumption of latency-and energy-related devices [2, 5]-[8].

The present surge in data size and use has led many academics to believe that improving the existing wireless system in many ways is the best way to achieve latency and energy goals. To address the increasing need for low latency and reduced energy usage, one solution is to install computer resources and caching at the network's edge [1, 9, 10].

High data speeds in cloud computing may be achieved by the use of large-scale signal processing amid blind signal separation, which is based on a pool of Base-band Processing Units (BPUs) [11], [12]. This makes advantage of statistical multiplexing, which allows for even more energy savings on a wide scale, in the processing [13]. Furthermore, the coexistence of heterogeneous nodes, such as User Equipment (UE) and Small Base Stations (SBSs), can enhance the throughput of Device-to-Device (D2D) communications. Additionally, it guarantees covering without seams [14].

The importance of progressive resource management, mobility management, networking, and localization is highlighted by the fact that the rigorous requirements of 5G cannot be addressed only by assuming resources for computation and heterogeneous nodes. The wireless communication system's performance may be enhanced by making proper use of resources through the scaling network [15]. Some machine learning algorithms are unable to interpret or make use of meaningful data from wireless networks in its raw form, leading to the loss of potentially useful information or patterns for modeling wireless systems. Heuristic and complex, Radio Resource Management (RRM) algorithms fall short of 5G's performance standards. So, in order for RRM algorithms to find better answers, a number of studies have looked at expanding the scope of optimal and sub-optimal solutions. However, most 5G networks have complicated network architecture and are quite vast in scale, which might lead to considerable complexity when creating algorithms. The current RRM algorithms aren't up to the task of handling dynamic networks like 5G and 6G because of how long it takes to make decisions. Centralized methods are impractical in 5G networks owing to the high computing power and huge expense associated with the vast number of nodes, as stated by the authors in [16]. So, it's ideal if nodes in the network can base their decisions on what they see close to home. To take advantage of adjacent calculations, the system can leverage ML methods implemented at the user level near the network edge (Edge computing).

Intelligent 6G networks enabled by ML are the focus of this essay, which also draws attention to the difficulties in studying these networks. Next, the study delves into the ins and outs of machine learning, covering both its applications and its underlying infrastructure. By comparing application-level and infrastructure-level performance matrices such as power allocation, resource management, caching, energy efficiency, etc., the article takes into account meeting the demand for network capacity, low latency, minimum processing time, and security of the communication system.

Several recent publications have examined and analyzed significant issues pertaining to the use and deployment of ML over wireless networks, including [3], [17] and [18]. According to [19], the incorporation of ML into the wireless core and edge architecture allows next-generation wireless networks to impact intelligent operations. 6G research and future plans were the primary topics of the writers in [20]. According to the authors, 6G is all about machine learning and artificial intelligence, which demand more research into the many levels of wireless communication models. This encompasses knowledge of data mining on the network, physical layer signal processing, etc. In addition, the authors of [21] presented the 6G vision as a complex network with three main components: the user side, the air interface, and the network edge. Core 6G enablers, according to their continuing development, are new paradigms of ML with communication networks.

## 2. CONTEXT AND INSPIRATION

In order to meet the high standards of Quality of Service (QoS) and to accommodate a wide range of applications, including real-time Virtual Reality (VR) applications, researchers are exploring uncharted technological territory in preparation for future wireless systems, such as

5G and 6G. One example of a physical layer technology for 5G networks is millimeter wave (mm-Wave) with massive multiplexing (Ma-MIMO). New 6G wireless systems will also rely heavily on ML for the physical layer, transceiver design, network, and application layers, expanding upon previous 5G systems. The idea of using ML approaches to wireless communication is somewhat new, but ML techniques have long been employed in image processing and computer vision. Possible applications of ML approaches for next-generation wireless include answering challenges like how to improve network-layer protocols and how to estimate and allocate wireless channels systems. In order to provide answers to the concerns posed above, this article will examine the function of different ML approaches in 5G and future wireless communication systems.

Based on the reasons given earlier, we have also concentrated on outlining the 6G progression towards ML and AI, as shown in Figure 1. A large body of literature has focused on the necessity of merging ML and AI, as well as the numerous smart areas that have benefited from this merging, such as healthcare, business and entertainment, speech recognition, medical systems, and intelligent search engines [22]. In their discussion of the state of technology today, the authors brought up some of the future possibilities, including ubiquitous connectivity, wellness apps, e-Health, holographic telepresence in smart environments, virtual reality, augmented reality, enormous mobility, and industry 4.0 and massive robotics. As a result, all of these uses necessitate improved wireless communication in order to facilitate the enormous data interchange across diverse devices, networks, and apps. Therefore, 6G wireless networks utilizing a variety of state-of-the-art technologies must provide broadband wireless connections that are real-time, dynamic, fast, dependable, near-instant, and available over a wide range of frequency spectrums [23], [24].

Developing a foundational understanding of ML approaches for use in wireless system design, including channel modeling, channel estimation, transceiver design, and novel user applications, is the driving force behind this article. The idea behind this is to create autonomous wireless networks that can take use of their resources without much help from humans. Ultimately, we want to enhance people's quality of life by providing greater QoS.

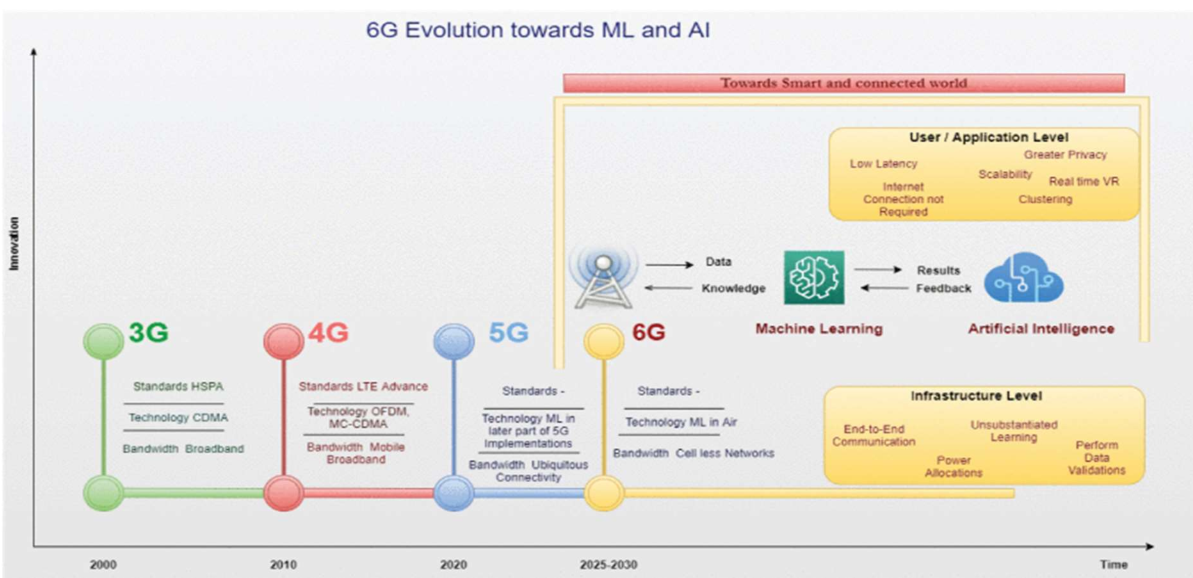


*Figure 1 Communication development and the possible use of ML methods in the next-gen wireless network*

## 3. AN OVERVIEW OF ML METHODS

When a mathematical model fails to capture all of a system's distinguishing characteristics, computational systems known as machine learning (ML) models step in. Regression, categorization, and intelligent agent–environment interactions are typical applications of these models. Models can make good decisions with unknown data and do calculations-based tasks after they have been trained on the provided data. In order to maintain

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existing Key Performance Indicators (KPIs) within established thresholds, this will enable ML modeling for mobility, availability, accessibility, and management of network communication based on 6G data. Additionally, it will improve and automate network performance management. 6G mobile networks with smart adaptive cells may also be managed with the help of ML. These areas will see significant improvements: maintenance, operation, power control, beam management, power savings, fault management, network configuration, quality of service prediction, throughput, and coverage performance. In Figure 4, we can see how ML improves 6G network performance control.

There are three main approaches to machine learning. The first is supervised learning, where the model is trained using input samples and their outputs. The second is unsupervised learning, where the model learns to differentiate between input samples without output labels. The third is reinforcement learning, where an agent interacts with its environment to learn how to translate each input into an action. Figure 2 shows an updated parallel processing framework in action with an artificial neural network (ANN).

6G wireless networks rely on ML since it can model non-mathematical processes. Additionally, certain ML techniques are already being utilized to replace heuristic or brute-force algorithms in order to discover the best solutions for network issues. With the advancement of ML in 6G networks, automatic zero-contact operation and control, as well as real-time monitoring, will become a reality. Mobile devices are an essential component of the infrastructure since they can make ML predictions and communicate them to the network for resource management purposes. Orchestration, network management, adaptive beam forming methods, and radio interface optimization are just a few of the many responsibilities that 6G network ML agents will have. Data from different networks and domains is brought together by such capabilities. In Figure 3, we can see how ML functions in 6G networks.

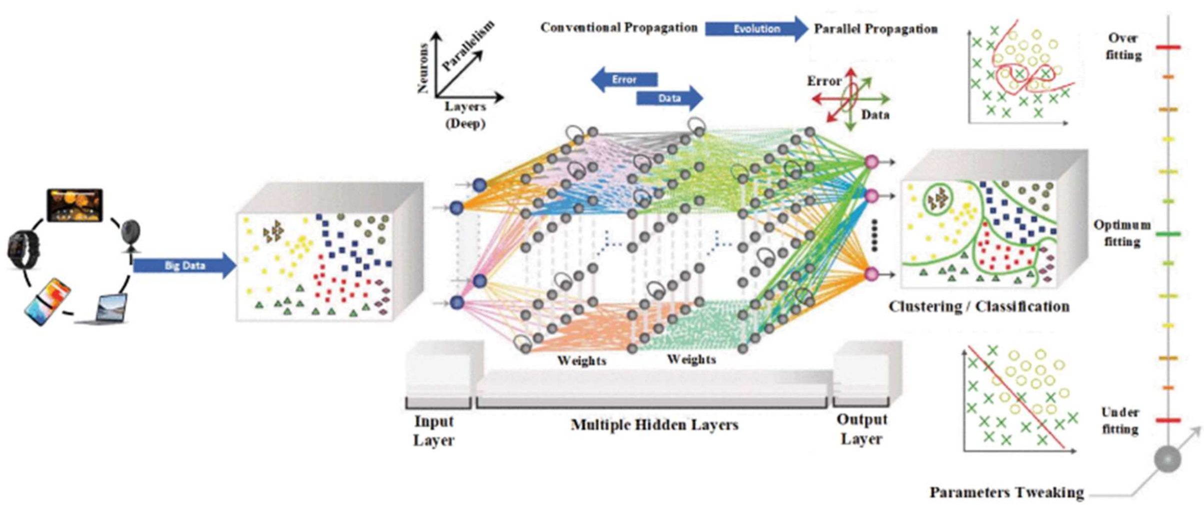


*Figure 2 AI Running on a Parallel Processing Framework for Machine Learning*

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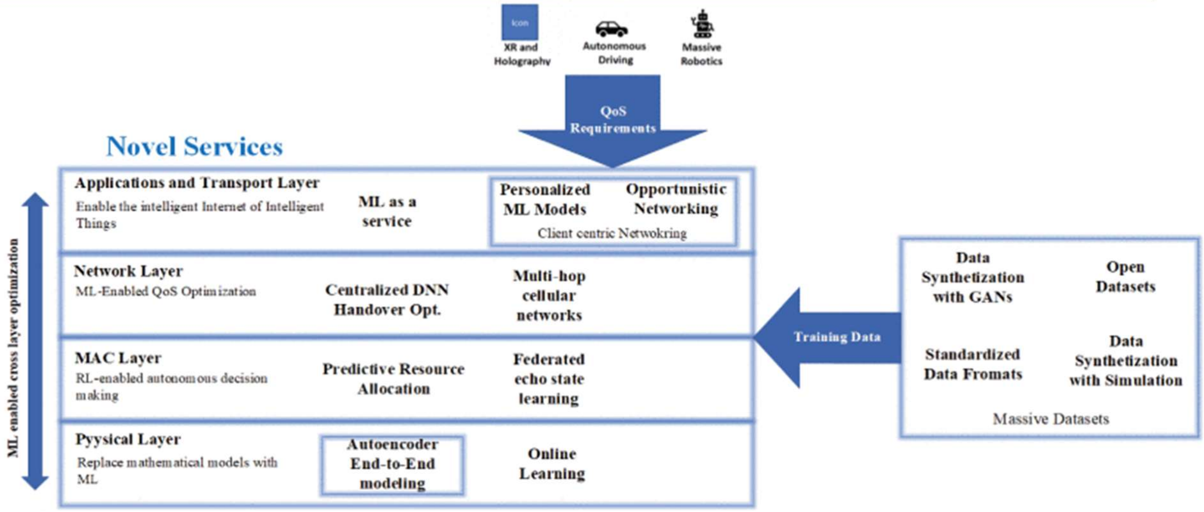


*Figure 3 Machine learning for communication wireless networks*

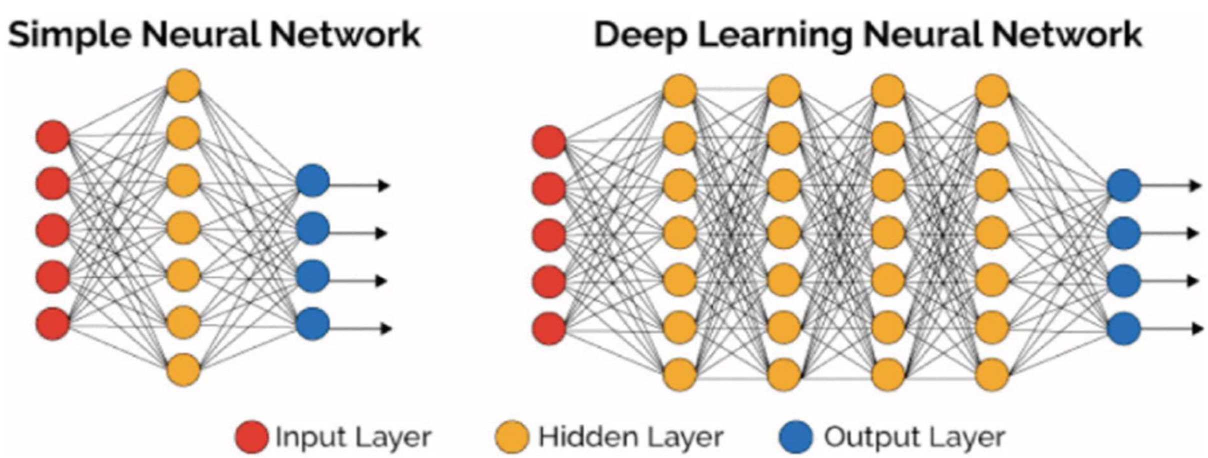


*Figure 4 A model that uses deep learning*

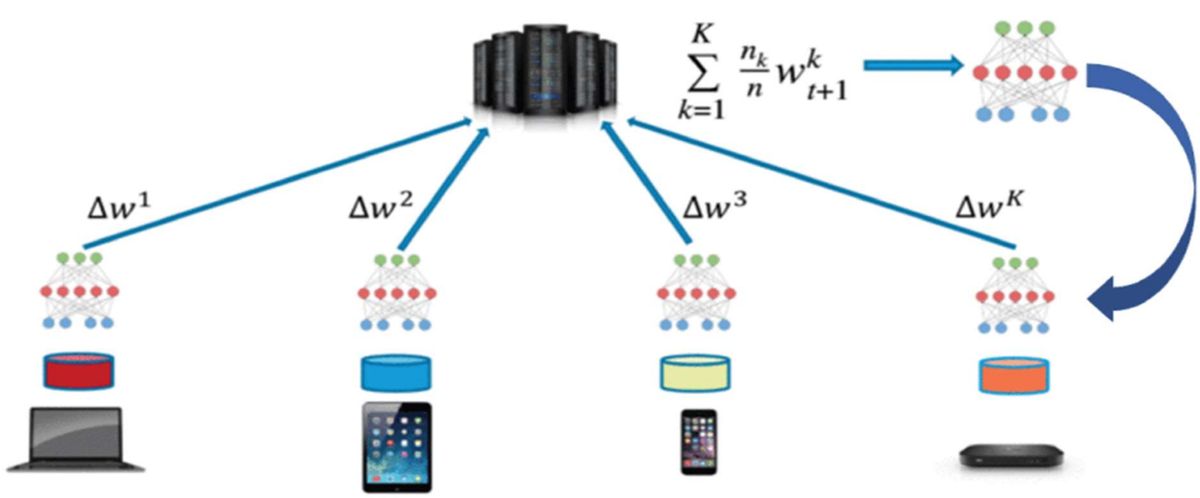

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*Figure 5 Introducing Federated Learning with this example.*

A subfield of artificial intelligence, deep learning models how human brains work and then uses that knowledge to generate patterns using multi-layered artificial neural networks. Common deep learning approaches include convolutional neural networks (CNN), long short-term memory (LSTM), recurrent neural networks (RNN), and deep neural networks (DNN).

### 3.1 Deep Learning (DL)

Figure 4 depicts the theoretical workflow of DL, whereby the iterative technique is carried out via hidden layers. Machines may learn the basics at the first level, and as they progress through the stages, more complex data is added. The input data is merged with the new data with each iteration, and the output data is the sum of all the input data.

### 3.2 Federated Learning (FL)

FL stands for "collaborative learning," a method by which a network's numerous distributed servers or edge devices work together to train and update an algorithm. FL instead distributes the model with the other participating servers or devices rather than exchanging the local data samples across edge devices. As seen in Figure 14, federated learning (FL) is a process. The Figure 5 shows the process of federated learning (FL).

### 3.3 Future Vision of Communication Networks

Performance measures with 6G aspirations and potential design issues within these measurements are described in this section. Also, two main points are covered in this section. While wireless technology has seen a lot of advancement, very few performance requirements have been raised as a result of these innovations [14]. Considering and mapping out the performance criteria for 6G includes things like peak throughput, improved energy efficiency, always-on connectivity, new ideas and technologies, and a self-aggregating communications fabric.

With the widespread rollout of 5G wireless networks, a new generation of mobile communication technologies is required. A lot of studies are looking at 5G's potential next iteration, 6G. The authors foresee 6G's future using innovative methods, intelligent connection, cell-less networks, seamless coverage, and a dispersed antenna system.

## 4. MACHINE LEARNING'S FUNCTION IN APPLICATION AND INFRASTRUCTURE

Power allocation, caching, load balancing, and clustering are some of the application and infrastructure level ML approaches described in this section. The primary objective of this part is to provide additional details on how 6G networks may make better use of ML for the benefit of users and how these networks can better handle the difficulties and expectations of users in the future.

In order to fulfill the increasing needs for low latency and quicker processing, ML has introduced revolutionary changes at the application level through its powerful features, such as exploiting user location to deliver sensitive information and conducting facial recognition, etc. [19]. Effective resource management, job automation, and improved security and safety through ubiquitous and continuous monitoring are the key goals of the application layer, which acts as the interface between the user and smart applications. The aforementioned performance measures can be attained by controlling the living environment of inhabitants using actuators or by installing applications directly on smartphones, which have built-in deep learning algorithms [17].

Intelligent caching and contents prediction are two areas where ML at the application level use supervised learning. The utilization of satellite connections to provide coverage throughout the whole global network is a prime example. These connections allow for low-latency communication even in faraway places. Secondly, ML uses techniques like neural networks and radio access networks (CRAN) to forecast contents and mobility patterns, and it uses this information to establish user associations with base stations (BSs). This is done with an eye on allocating power among the 6G wireless resources. Optimal resource allocation in networks may be achieved by grouping or clustering nodes or points at higher levels using supervised and unsupervised learning. Additionally, there are a number of possible uses for clustering in data analysis, such as analyzing trends in social networks from the

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network side, analyzing data from phone apps from both the user and the network side, and rating online resources.

Present-day ML techniques designed for batch processing do not meet the needs of real-time data processing applications. Such streaming data applications are well-suited to online teaching. But there's a strict time constraint on how long each data sample may be processed in online training. Intelligent caching and channel tracking are two common examples of communication system applications of online and offline learning. Typically, user-level reinforcement learning maximizes computing efficiency by optimizing performance indices using existing objective functions.

### 4.1 Examining a Real-World Example of Biometric Application and Infrastructure

Matching and liveness detection are executed centrally on the server-side, where the biometric application template is kept. The verification attempts are forwarded to a central matching engine, which stores all of the processing against a central template on the server. The demand for client-server applications is declining in large sectors like healthcare and finance, mainly because of server-centric issues with networking and security. All operations take place on the device itself at this level of AI, including creating, storing, and matching biometric templates. Access to the private key, which is kept on the device, is provided in the quick identify online system (FIDO). Many industries, including healthcare and banking, are leaning toward a "one size fits all" approach to data management in anticipation of the impending smart city boom. Companies in the healthcare and financial industries, which are subject to stringent regulations, may be hesitant to use a "one size fits all" approach. In this setup, a hardware original equipment manufacturer (OEM) handles the collection and storage of biometric identification data using algorithms that prioritize convenience above security.

At the application level, current ML algorithms lack effectiveness and external validity, while they may detect analytical regularities in massive data sets. Additional investigation is required to provide a framework for integrating ML and 6G wireless connectivity into different applications. Additionally, we are looking into ways to implement the training data reduction approach at higher levels in order to create a completely autonomous system.

The design of future wireless communication systems would need massive amounts of channel data and suitable channel models grounded on statistical approaches; yet, ML techniques are being employed for managing enormous data. At present, channel modeling allows for high bandwidth transmission in wireless communications. Yet another path lies ahead, driven by the growing need of effective channel allocation and channel modeling in light of 6G and the Internet of Things.

## 5. CONCLUSION

Several ML methods and how they function have been covered in this article. Along with the benefits, drawbacks, and potential of the 6G communication technology, we have also discussed its future plans. We then went on to discuss the 6G future vision and how ML at the application and infrastructure levels may be more productive in order to tackle the 6G issues of the future. Here we examine and compare the existing demand for 6G with the state-of-the-art. Based on the evaluation, application level solutions are more suited to address the gaps caused by 6G issues than infrastructure level ones. We have covered the case study-biometric application, followed by best fit. Both the application and infrastructure levels of smart biometric application functionality are demonstrated in the case study. So far, we have pinpointed the potential future applications of ML in areas such as channel modeling, data reduction, power allocation, and resource management. 6G wireless communication networks allow for the intelligent execution of several ML algorithms. As a result, in order to improve smart applications for both present and future 6G networks, we need to find a way to address issues like latency, power allocation, privacy, security, model interoperability.

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