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OVERVIEW

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Evolution toward intelligent communications: Impact of deep learning applications on the future of 6G technology

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Abstract

The sixth generation (6G) represents the next evolution in wireless communication technology and is currently under research and development. It is expected to deliver faster speeds, reduced latency, and greater capacity compared to the current 5G wireless technology. 6G is envisioned as a technology capable of establishing a fully data-driven network, proficient in analyzing and optimizing end-to-end behavior and handling massive volumes of real-time

Abbreviations: 6G, sixth generation; ACDRA, AI-driven collaborative, dynamic resource allocation; AI, artificial intelligence; AMP, approximate message passing; AN, artificial noise; AoAs/AoDs, angles of arrivals/departures; ARAN, aerial radio access networks; CAV, connected autonomous driving; CHERA, clustering-based heuristic edge resource allocation algorithm; CJ, cooperative jammer; CNNs, convolutional neural networks; CRBFT, credit reinforce Byzantine fault tolerance; CRNs, cognitive radio networks; CSI, channel state information; CT, computed tomography; DL, deep learning; DNN, deep neural network; DRAM, dynamic resource allocation method; DRL, deep reinforcement learning; EM, expectation–maximization; eMBB, enhanced mobile broadband; FC, fully-connected layers; FL, federated learning; GA, genetic algorithm; GABRA, genetic algorithm-based resource allocation algorithm; GAN, generative adversarial network; GRU, gated recurrent unit; GSA, greedy shrinkage algorithm; HA, heuristic algorithm; IIoT, Industrial IoT; IoMT, Internet of Medical Things; IoT, Internet of Things; IRS, reflecting surface; ITU, International Telecommunication Union; JADCE, joint activity detection and channel estimation; LADN, local alignment deep network; LoS, line of sight; LSTM, long short-term memory; M2M, machine-to-machine; MDP, Markov decision process; MEC, mobile edge computing; MINLP, mixed-integer nonlinear program; ML, machine learning; mMTC, massive machine-type communication; mmWave, millimeter-wave; MR, mixed reality; N2V, Noise2Void; NFV, network function visualization; QoS, quality of service; RL, reinforcement learning; RNN, recurrent neural network; SA, simulated annealing; SDN, software-defined networking; SE-Resnet, squeeze-and-excitation residual network; SR, social recommendation; THz, terahertz; UAV, unmanned aerial vehicles; URLLC, ultra-reliable low latency communication; V2V, vehicle-to-vehicle.

Mohamed Abd Elaziz and Mohammed A. A. Al-qaness contributed equally to this study.

data at rates of up to terabits per second (Tb/s). Moreover, 6G is designed to accommodate an average of 1000+ substantial connections per person over the course of a decade. The concept of a data-driven network introduces a new service paradigm, which offers fresh opportunities for applications within 6G wireless communication and network design in the future. This paper aims to provide a survey of existing applications of 6G that are based on deep learning techniques. It also explores the potential, essential technologies, scenarios, challenges, and related topics associated with 6G. These aspects are crucial for meeting the requirements for the development of future intelligent networks. Furthermore, this work delves into various research gaps between deep learning and 6G that remain unexplored. Different potential deep learning applications for 6G networks, including privacy, security, environmentally friendly communication, sustainability, and various wireless applications, are discussed. Additionally, we shed light on the challenges and future trends in this field.

This article is categorized under:
Technologies > Computational Intelligence
Fundamental Concepts of Data and Knowledge > Explainable AI
Technologies > Machine Learning

KEYWORDS

5G, 6G network, cybersecurity, deep learning, green communication, sustainability

1 | INTRODUCTION

The sixth-generation (6G) wireless network will be the next networking technology to deliver a universal connection. Compared to earlier networking technologies, this developing technology has various characteristics, including deep holographic communication, artificial intelligence (AI), visible light communication, 3D coverage frame, and ground and aerial wireless hotspots enabling cloud functionality (Attiya et al., 2022; Zhao et al., 2021). The total reliance on AI and its different technologies to operate such a vast networking architecture is one of the most impactful of these qualities (Huang et al., 2019; Ikotun et al., 2022).

In May 2019, the International Telecommunication Union (ITU) released the IMT-2030 standard, stating that 6G aspires to create a revolutionary user experience and a new set of sensory information and experiences. 6G will be a hybrid system that combines numerous networks, including local, mobile cellular, satellites, ocean, and other yet-to-be-determined networks (Lu & Zheng, 2020). The 6G will use novel communication mechanisms unconstrained by existing network technology or concepts. To accommodate existing and future scenarios, it incorporates entirely compatible new concepts, systems, solutions, and protocols. Simply, the 6G can be considered as a ubiquitous, intelligent, deep, and holographic connectivity-based system. The 6G is an intelligence-based system that will use artificial intelligence-based methods. Specifically, deep connectivity represents deep learning, deep mind, and deep sensing. For more information, authors in Banafaa, Shayea, et al. (2022) provide a brief review of 6G mobile communication technology.

1.1 | Motivation

In the literature, a few survey studies have been presented for the 6G. For example, Zhao (2019) presented a survey on intelligent reflecting surfaces toward 6G. Tang et al. (2021) presented a survey study that addresses the applications of machine learning for end-to-end communications toward 6G. Lu and Zheng (2020) presented a comprehensive survey on 6G challenges, technologies, and related issues. They addressed different aspects of the 6G. Salh et al. (2021)

summarized the applications of deep learning techniques on for ultra-reliable and low-latency Communication on 6G wireless networks. In Nguyen, Lin, et al. (2021), the authors presented a survey on the privacy and security issues for 6G. However, they summarized the recent studies of the existing networks, such as the 5G. Sun et al. (2020) summarized the recent applications of machine learning for the privacy of different networks toward 6G. Dao et al. (2021) presented a survey on aerial radio access networks (ARAN), and their potential applications on the 6G in the future. Jiang et al. (2021) presented a comprehensive survey study to give a picture of the 6G in terms of architecture, use cases, usage scenarios, requirements, drivers, enabling technologies, and key performance indicators. De Alwis et al. (2021) presented a survey of the recent developments toward 6G.

They highlighted the technological and societal trends which initiated the drive toward 6G. They also described the necessary requirements for realizing the applications of the 6G. Nguyen, Ding, et al. (2021) highlighted some fundamental 6G techniques that may be applied to develop the future of the Internet of Things (IoT) networks.

Table 1 summarizes the difference between our paper and the survey mentioned above papers. Compared to the recently published surveys and the best of the author's knowledge, this is the first survey that focuses on the applications of 6G using deep learning (DL) techniques. As mentioned earlier, the 6G is an intelligence-based system that will use artificial intelligence-based methods. Specifically, deep connectivity represents deep learning, mind, and deep sensing.

1.2 | Key contributions

The current survey focuses on deep learning techniques used in 6G networks and their applications. More so, the paper provides a comprehensive and detailed discussion of the architectures of the 6G infrastructure, deep learning technologies, security, and privacy issues of 6G, sustainability, advanced applications, and others.

Moreover, we summarize many published articles related to the 6G in recent years. Additionally, we discuss future directions and opportunities. To sum up, the main objectives and contributions of this survey are presented as follows:

- We present a comprehensive survey on the applications of artificial intelligence methods for the 6G by summarizing the related published studies and categorizing them according to their applications.
- We present a detailed discussion of the applications of deep learning methods for 6G wireless networks, including their possible and existing applications such as security, privacy, sustainability, wireless communication, and green 6G.
- We highlight the critical challenges that require further investigation using advanced deep learning-based solutions and methods.
- We discuss the research challenges and study the fundamental concepts and techniques that 6G deep learning-based methods should be adopted and the current challenges that should be further studied.
- We recommend some future research directions to boost the efficiency of the DL methods for 6G applications.

1.3 | Paper organization

In this paper, we collect the relevant studies and categorize them into several categories. As shown from Figures 1 and 2 show the number of recently published studies (collected from the Web of Science) for the 6G network and deep learning for 6G, respectively. The collected papers are described and categorized in this survey paper as follows. Section 2 presents a quick review of the current generation 5G. More so, it presents a comprehensive overview of the 6G. Section 3 presents a detailed description of the most well-known deep learning methods, such as Convolutional Neural Networks, Recurrent Neural Networks, and other neural networks. Section 4 presents the core section of this paper, which is the applications of deep learning for the 6G. It summarizes the applications of deep learning for network security and privacy, including the possible applications for 6G. Also, it presents the applications of deep learning for 6G sustainability and Wireless communication. Section 5 summarizes the opportunities and challenges that should be further investigated in future studies. Finally, Section 6 concludes this survey paper.

2 | OVERVIEW OF 6G

In this section, we briefly introduce the 6G technology and its previous generations.

TABLE 1 Comparison to similar survey papers for 6G.

Reference	Main application	DL for green 6G	DL for 6G security	DL for 6G privacy	DL for 6G wireless	DL for 6G sustainability	Description
Zhao (2019)	Intelligent reflecting surfaces toward 6G	No	No	No	No	No	It focuses only on a specific point of intelligent reflecting surfaces
Tang et al. (2021)	Machine learning for 6G. Network Access Routing to Traffic Control and Streaming Adaption	No	No	No	No	No	Most of these applications are not related to the new 6G. There are four existing networks. So, we did not consider them in this survey
Lu and Zheng (2020)	A general survey on identify 6G and its related issues	No	Yes	Yes	No	No	It focuses more on the potential structure and applications of 6G and its related applications
Salh et al. (2021)	Deep Learning for Ultra-Reliable and Low-Latency Communications Challenges on 6G Wireless Systems	No	No	No	No	Yes	It focuses on a specific point. However, the collected papers are related to previous network structures
Sun et al. (2020)	The applications of machine learning for the privacy of 6G	No	Yes	Yes	No	No	It focuses only on privacy and partially for security of the 6G
Dao et al. (2021)	Survey on ARAN and their potential applications on the 6G	No	No	No	No	No	It focuses only on the ARAN
Jiang et al. (2021)	General survey on the 6G	No	No	No	No	No	A general survey that focuses on general structure, and applications of 6G network
De Alwis et al. (2021)	General survey on the structure and technologies of the 6G	No	No	No	No	No	A general survey that focuses on general structure, and potential technologies of the 6G network
Nguyen, Ding, et al. (2021)	The applications of 6G for IoT applications	No	No	No	No	No	It focuses on the applications of 6G for IoT applications. It is worth mentioning almost of the mentioned applications are for existing networks
Our	Main applications of deep learning for 6G	Yes	Yes	Yes	Yes	Yes	The main goal of this survey is to cover the applications of DL for 6G

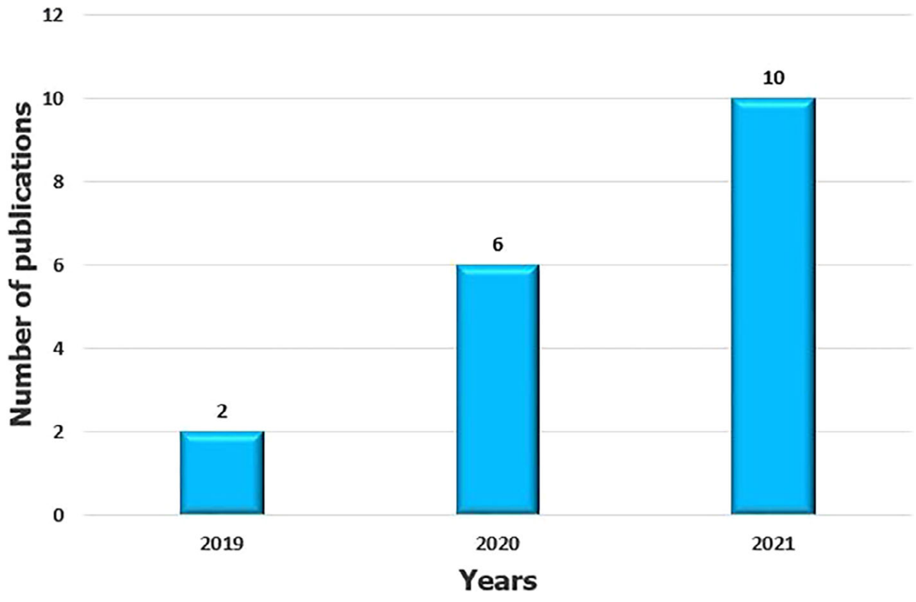

FIGURE 1 6G networks.

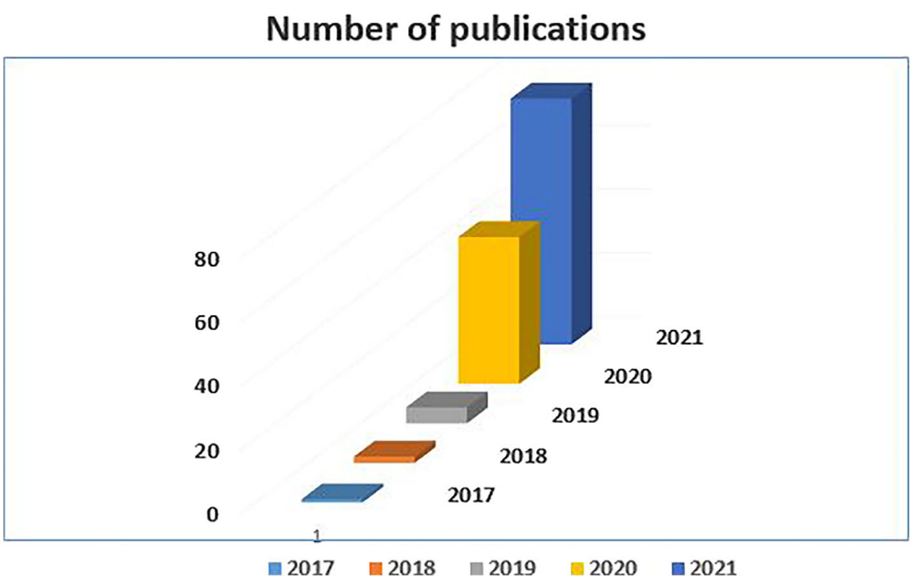

FIGURE 2 6G with deep learning.

2.1 | 5G generation

The 5G networks have recently begun to spread around the globe (Hui et al., 2020). The 5G networks enable larger capacities, higher data rates, reduced latency, massive device connectivity, lower cost, and better consistent quality of service than 4G networks, thanks to sophisticated access control and network optimization technology (Gupta & Jha, 2015). The adoption of 5G will contribute to a growth in the use of various IoT applications that require highly high connection, security, and low latency (Li, Da, & L. and Zhao, S., 2018).

In general, the sub-GHz, 1–6 GHz, and above 6 GHz frequency bands make up the 5G spectrum (Zhang, Liang, & Niyato, 2019). Due to the excellent attenuation properties of the signals conveyed at these frequencies, sub-GHz bands are suitable for providing wide coverage for machine-type devices in IoT. For 5G services, the 1–6 GHz bands provide a good blend of coverage and data rate. Large bandwidths exist in spectrum bands above 6 GHz, allowing for high data rates to support enhanced mobile broadband (eMBB) applications within a narrow coverage area.

In addition, within a single 5G core network, 5G is designed to meet various needs from multiple applications. As a result, the 5G core network will need to support several new features, including flexible resource allocation, network reconfiguration, and open access to various platforms. Mobile edge computing (MEC), software-defined networking (SDN), network function visualization (NFV), and network slicing are examples of typical 5G core network evolution.

2.2 | 6G generation

The plentiful bandwidth of THz must be used to ensure a high rate and reliability. The 5G network, on the other hand, enables a Gbps enhanced mobile broadband (eMBB) speed, massive machine-type communication (mMTC), and a microsecond latency of 99.99% of the level of ultra-reliable and low latency communication (URLLC) transmissions to fulfill the information civilization's needs through 6G technology (Zhu et al., 2019). Redesigning the physical layer and enabling technologies, such as packet and frame structure, is required to ensure high dependability (Sun et al., 2019). The THz spectrum is expected to provide a Tbps data rate to meet extremely high URLLC, giving 6G wireless networks higher sensing resolution and positioning accuracy. The more bandwidth capacity increases, the more big data in 6G becomes possible, theoretically achievable by using a sub-THz radio spectrum above 90 GHz. The use of intelligence in the architecture of 6G wireless networks, on the other hand, is expected to give high data rates with minimal latency (Al-Sai et al., 2022; Chen et al., 2019).

Moreover, the 6G will experiment with novel communication mechanisms unconstrained by existing network concepts or technology. It incorporates entirely compatible new concepts, systems, protocols, and solutions to accommodate existing and future scenarios. Intelligent, deep, holographic, and pervasive connectivity are all part of the 6G system. The intelligence of the network elements and network architecture, the connected object (the terminal device), and the information conveyed to enable the intelligent service are all reflected in intelligent connectivity. Deep sensing, deep learning, and deep mind are examples of deep connectedness. Holographic communication anywhere (and at any time), high-fidelity and seamless coverage AR/VR/XR are all properties of holographic connectivity. Ubiquitous connectivity is a multi-dimensional coverage link that spans all terrains and spaces (Nawaz et al., 2019).

The 6G technology has become a concern of academia, industry, government departments, and even the general public as a phrase with a significant search volume. In addition, numerous countries have begun work on 6G (Lade et al., 2017; Zhang, Liang, & Niyato, 2019). Many experts believe that most of the current 5G technology characteristics will be kept and enhanced in the 6G system. Furthermore, 6G will introduce even more revolutionary core technologies. Future objects, in other words, are viewed as links between various technologies, such as intelligent connectivity, deep connectivity, holographic connectivity, and ubiquitous connectivity. Figure 3 depicts the vision for 6G technology.

Even though 5G delivers ultra-reliable low latency communication (URLLC), it has several drawbacks, according to Zong et al. (2019), such as the fragility of short-packet, sensing-based URLLC. Low-latency services with high data rates, which are critical for AR, mixed reality (MR), and virtual reality (VR), may be limited due to this. Furthermore, intelligent gadgets are predicted to increase data traffic tenfold, necessitating high-speed data transfer, which is not addressed in 5G specifications (Elmeadawy & Shubair, 2020). Similarly, modern IoT technologies that necessitate the convergence of communication, detection, control, and computation capabilities are not supported by 5G.

According to Zong et al. (2019), even though 5G provides URLLC, it has some limitations, such as the weakness of short-packet, sensing-based URLLC. This can restrict the reliability of low-latency services with high data rates essential for AR, mixed reality (MR), and VR. Additionally, smart devices are expected to increase data traffic exponentially and require high-speed data transfer, which is overlooked in 5G standards (Elmeadawy & Shubair, 2020). Likewise, 5G lacks support for advanced IoT technologies requiring the convergence of communication, detection, control, and computing functions. As a result, 6G becomes necessary to enable various IoT technologies.

Table 2 compares the technical specifications of 5G and 6G by Elmeadawy and Shubair (2020). The 6G will be able to provide improved dependability, lower latency, and full integration with AI, extended reality (XR), IoT, and blockchain technologies when compared to 5G (Lu & Zheng, 2020). In addition, the 6G mobile technology will not only improve upon the intelligence, reliability, scalability, and security of current mobile networks but will also enable satellite communication integration to create an all-encompassing mobile network (Akyildiz et al., 2020). This is necessary to achieve a truly global wireless network presence. Therefore, many solutions have been proposed and investigated for the vision, specifications, requirements, and expected technologies for 6G. To meet the goals of 6G and address the limitations of 5G, new and advanced features must be added to mobile communication systems. 6G

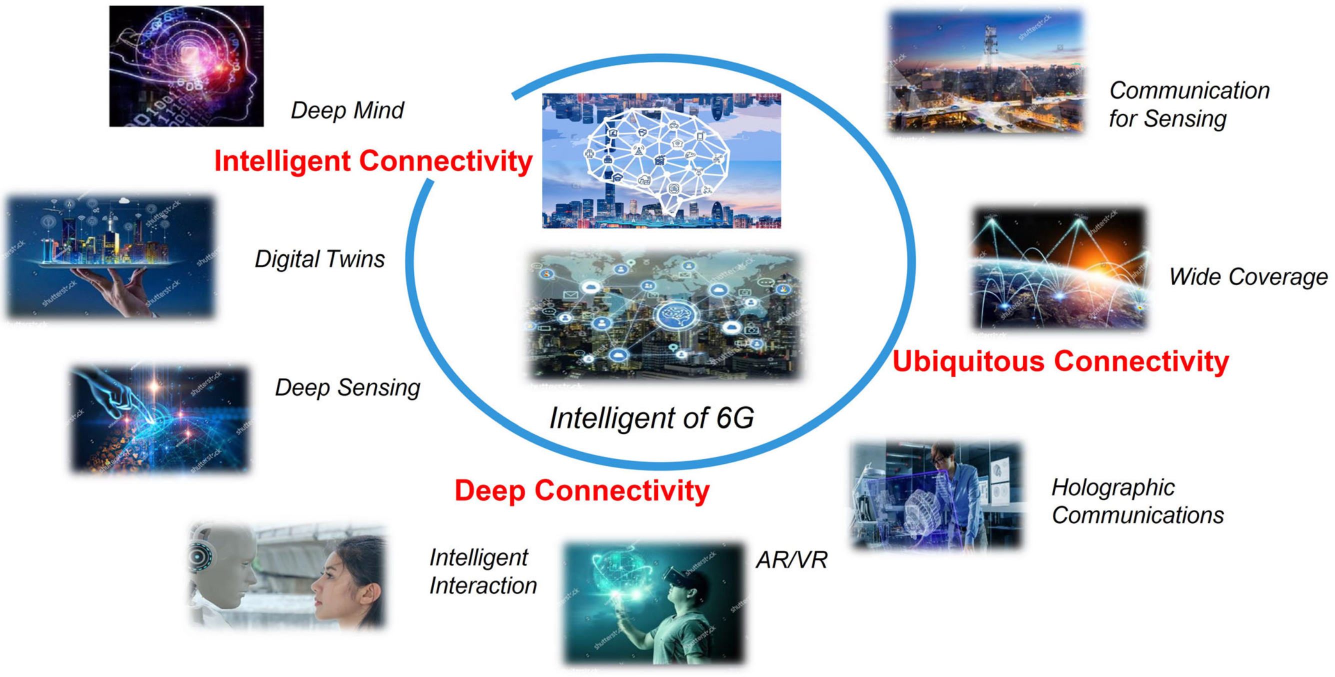

FIGURE 3 Vision of 6G networks.

TABLE 2 Comparison between 5G and 6G caption.

Characteristic	5G	6G
Operating frequency	3–300 GHz	Up to 1 THz
Uplink data rate	10 Gbps	1 Tbps
Downlink data rate	20 Gbps	1 Tbps
Automation integration	Partial	Full
Spectral efficiency	10 bps/Hz/m^2	1000 bps/Hz/m^2
U-plane latency	0.5 ms	0.1 ms
Maximum mobility	500 km/h	1000 km/h
Localization precision	10 cm on 2D	1 cm on 3D
Uniform user experience	50 Mbps 2D	10 Gbps 3D
C-plane latency	10 ms	1 ms
Reliability	10–5	10–9
Processing delay	100 ns	10 ns
Traffic capacity	10 Mbps/m^2	1–10 Gbps/m^2
Haptic communication integration	Partial	Full
XR integration	Partial	Full
Center of gravity	User	Service
Time buffer	Not real time	Real time
Satellite integration	None	Full
AI integration	Partial	Full
Dynamic spectrum sharing	Sub-Ghz and 1–6 Ghz	Terahertz channel estimation
Authentication and access control	Meter-level	Centimeter-level
Jitter	Not specified	1 μs

networks will introduce a range of new technologies such as a THz-band operating system, efficient resource allocation, widespread use of AI, automation of networks, intelligent network environments, ambient backscatter communication, Internet of Space Things (IoST), large-scale MIMO cellular networks, and human-to-human (H2H) communication (Saad et al., 2019).

3 | OVERVIEW OF DEEP LEARNING

In this section, we will briefly describe the most commonly used deep learning architectures and techniques in the field of 6G. The core differences between DL models can be evaluated based on various criteria, including the architecture, the building blocks or units, the training process, the way of learning the features, input representations, performance, computational consumption, latency, and the deployment in embedded or edge systems when it is related to 6G applications. We will shed light on the criteria mentioned above in the following sections.

Various connected processing layers distributed sequentially or parallel are used to process the input data, eventually building the DL model. Stacking or combining different processing units helps the DL models model the data and learn complex and abstract features. Thus, different DL models can be formed and trained based on the data type, which can vary between different applications such as text, image, and audio (Abualigah, Gandomi, et al., 2021). The variation in data types allows the use of different DL models in various research areas, including 6G. Furthermore, the developed DL models can be interchangeably used to tackle problems in many areas, such as language modeling (Du et al., 2021; Lei, 2021), object detection (Wang, Bochkovskiy, & Liao, 2021), recommendation systems (Caren Han et al., 2021), and wireless communications (Hares et al., 2021). Related to some of the criteria mentioned above, the evolution in big data, edge, and cloud computing, and the development in artificial intelligence (AI) research reshaped the integration of DL models in the field of 6G. Thus, the emergence of all these fields has allowed using DL models to overcome issues encountered in the 6G field, such as computation resources, communication optimization, latency, and data transmission and storage. In addition, DL models are known for their ability to automatically learn, predict, and adapt when new data (structured or unstructured data) is available. Although the existing DL models have shown remarkable performance in many research fields, the build, training, and optimization of such models is still a challenge and a fertile ground for further evolution. Most DL-based solutions can share features such as feature extraction and learning from noisy data, pattern recognition in training samples, data classification, and the ability to adapt to new data and environments automatically.

Convolutional neural networks (CNNs) are among the most popular deep learning architectures that feature extractors. The ability of CNNs to perform automatic feature engineering actions without human intervention made the CNNs the popular networks in many research fields, including bioinformatics (Nigam et al., 2019), robotics (Shukla et al., 2020), health-care (Yuan et al., 2014), and especially in computer vision (Dai et al., 2021). DL models such as CNNs have shown remarkable performance in many fields; their ability to automatically learn and adapt from data is still a challenging task in setting up the model architecture, building block structure, learning mechanism, and hyper-parameter selection. For instance, CNN's can heavily rely on parameters such as the number of convolutional layers, the number of filters, and the size of filters to learn and extract the features. In addition, other DL networks can also be built using a variety of parameters such as the number of hidden layers, number of neurons in each layer, type of activation function, regularization technique, and optimization algorithm. Thus, the proposition or adaption of such DL networks needs to be performed mainly in a new field of research, such as 6G. In addition, most of the proposed DL models in 6G research areas are based on the same architecture and the exact learning mechanism proposed for different applications or based on the trial and error process. Thus, we can find a lack of a solid mathematical theory, network behavior interpretation, or explanations of the proposed DL models in 6G research areas. The following sections will describe the most commonly used DL models and their associated architecture and training process.

3.1 | Convolutional neural networks

CNN's are commonly used in areas such as computer vision and applied to applications such as visual recognition (Wang, Sun, et al., 2020), speech synthesis (Kumar et al., 2019), features extraction (Han et al., 2020), object detection

(Howard et al., 2019), transfer learning (Zhang et al., 2020), image classification (Tan & Le, 2021). The CNN can be composed of the following core building blocks: convolution, pooling, and fully connected. However, networks such as HRNet (Wang, Sun, et al., 2020), Ghostnet (Han et al., 2020), Resnest (Tan & Le, 2019; Zhang et al., 2020), and Efficientnetv2 (Tan & Le, 2021) have been proposed with different building blocks wherein some architectures such as Efficientnetv2 the traditional convolution layers are replaced with the bottleneck layers. In the traditional convolution layer, the network benefits from convolution operations applied at this layer on the input data, which allows the network to learn complex feature representations. The convolution operations result from a multiplication operation between the input data and the filters where the network learns the filters. A common structure of a CNN is to place a pooling layer after the convolutional layer to reduce the feature maps resulting from the convolution operation. For instance, the pooling layer can apply a function (max or average) that downsamples the size of the feature maps by a certain factor, such as two or four. The block consisting of the convolution and pooling layers can be repeated sequentially or in parallel much time based on the network complexity and size. A set of fully connected layers (FC) can be placed at the network's end to learn and perform the final classification at the end of the CNN structure. The FC layers are usually a linear layer and a non-linear activation function.

Efficient neural networks are a variation of CNNs, which have been ranked as state-of-the-art networks in various applications. These types of networks inherent many techniques and mechanisms from well-known architectures such as ResNet (Residual Networks) (He et al., 2016) and DenseNet (Huang et al., 2017). Efficient neural networks such as EfficientNet (Foret et al., 2020), Efficientnetv2 (Tan & Le, 2021), and MobileNetV3 (Howard et al., 2019) are well-known architectures built to optimize the network size and performance with their ability to be deployed in an embedded or edge system. Thus, smaller networks with high performance and low optimization costs have a great opportunity to be embedded in devices and systems related to 6G. The MobileNetV3 architecture and its core components are illustrated in Figure 4. ResNet (Residual Networks) (He et al., 2016) implements the residual blocks to reduce the network size and improve the performance where inside each residual block, a residual mapping is used to connect every few stacked layers, which is also known as skip connection mechanism. Meanwhile, EfficientNet comprises convolution layers scaled uniformly using a compound coefficient. The compound coefficient is applied to the input data depth, width, and resolution. In EfficientNet, a set of fixed scaling coefficients is selected using a small grid search. In addition, EfficientNet integrates blocks introduced in MobileNetV2 (Sandler et al., 2018) such as the inverted bottleneck residual blocks and squeeze-and-excitation (SE) blocks in their structure. The MobileNetV3 architecture uses building blocks

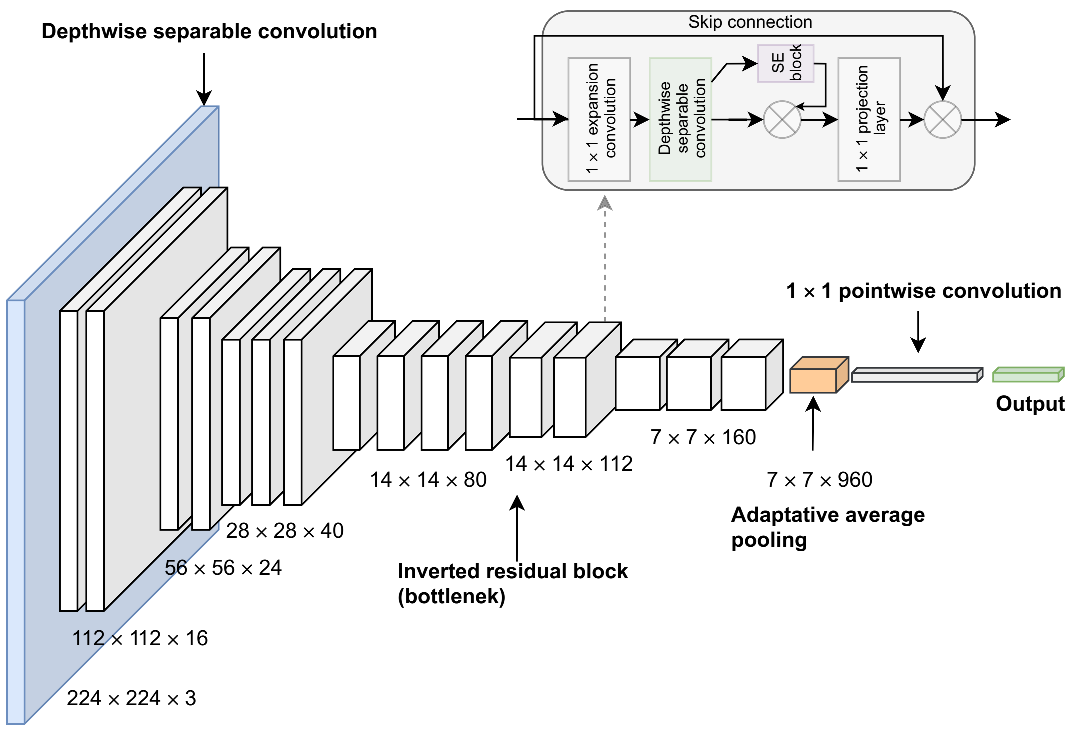

FIGURE 4 The MobileNetV3 architecture and its core components.

from its previous versions, including MobileNetV1 (Howard et al., 2017) and MobileNetV2. The blocks used to build MobileNetV3 were selected and optimized based on a network architecture search (NAS) algorithm called NetAdapt. The core building blocks used in MobileNetV3 are the depthwise separable convolutional layer, the 1×1 convolution (pointwise convolution) for linear combination computations, the global average pooling layer, the inverted residual block (He et al., 2016), the Squeeze-And-Excite block (SE block) (Tan et al., 2019), and the h-swish activation function (Elfwing et al., 2018; Ramachandran et al., 2017). Most of the networks mentioned above are released as pre-trained models where the training has been conducted using large datasets such as the ImageNet dataset (Krizhevsky et al., 2012). Other existing pre-trained models built using CNN or a modified architecture of CNNs are XceptionNet (Poma et al., 2020; Szegedy et al., 2015), CoAtNet (Dai et al., 2021), You only look once (YOLO) (Bochkovskiy et al., 2020; Ge et al., 2021), and FNet (Brock et al., 2021).

3.2 | Recurrent neural networks

In terms of sequence data processing, recurrent neural network (RNN) (Merity, 2019) are well-known deep neural networks used in applications such as machine translation (Ganapathy, 2020), language modeling (Melis et al., 2019), and time-series forecasting (Zhou, Zhang, et al., 2021). RNNs have various variants, including gated recurrent unit (GRU) and long short-term memory (LSTM), where the main difference is the RNN cell structure. The commonly used RNNs are inherited artificial neural networks (ANNs) that employ hidden states to reuse the information from the previous time step. The RNN learns the hidden states using the input data, where the network's output is the hidden state used to predict the next time step. The standard RNN structure comprises a set of gates represented with linear layers and non-linear activation functions stacked together. Meanwhile, the GRU is composed of two gates: the reset gate and the update gate, which is responsible for controlling the information flow. The reset gate can be seen as the network's term memory, while the update gate is the long-term memory. In contrast, the LSTM network has a cell structure composed of three gates, including an input gate, a forget gate, and an output gate. In LSTM, the hidden states are used as short-term memory, whereas the cell state is used as long-term memory. The forget gate is used to keep or discard the information from the previous time step. The input gate is used to assess the quality of the information from the input data. The output gate is used to predict the hidden state for the next time step. Mainly, the LSTM and GRU cell structures were explicitly designed to overcome the limitations of the standard RNNs, including the vanishing (or exploding) gradient, slow computation, and long-term dependency problems. Figures 5 and 6 illustrate the GRU and LSTM cell structures, respectively. To overcome the issues mentioned above, more solutions have been integrated into networks such as RNN, LSTM, and GRU, including the gradient clipping (Zhang, He, et al., 2019) and attention mechanism (Vaswani et al., 2017). Furthermore, complex network architectures have been designed using the Transformer-based structure (Vaswani et al., 2017), which mainly relies on encoder and decoder architecture. Other types of networks will be discussed in the next section.

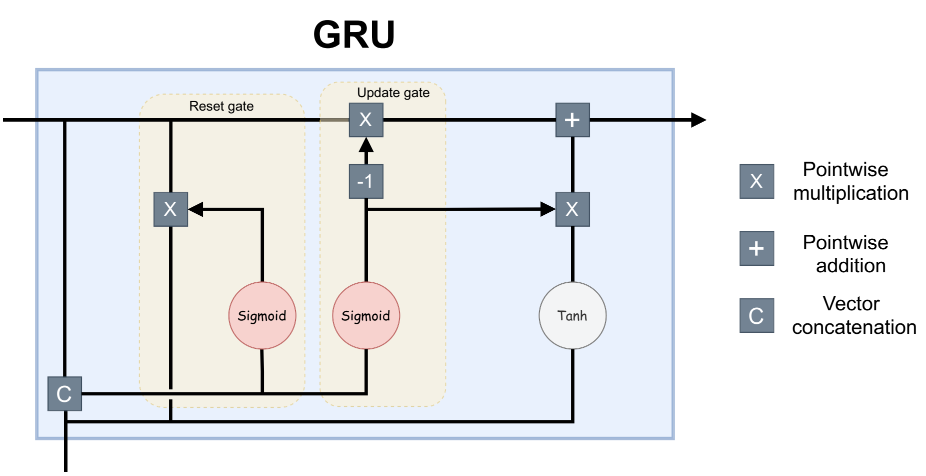

FIGURE 5 The GRU cell structure.

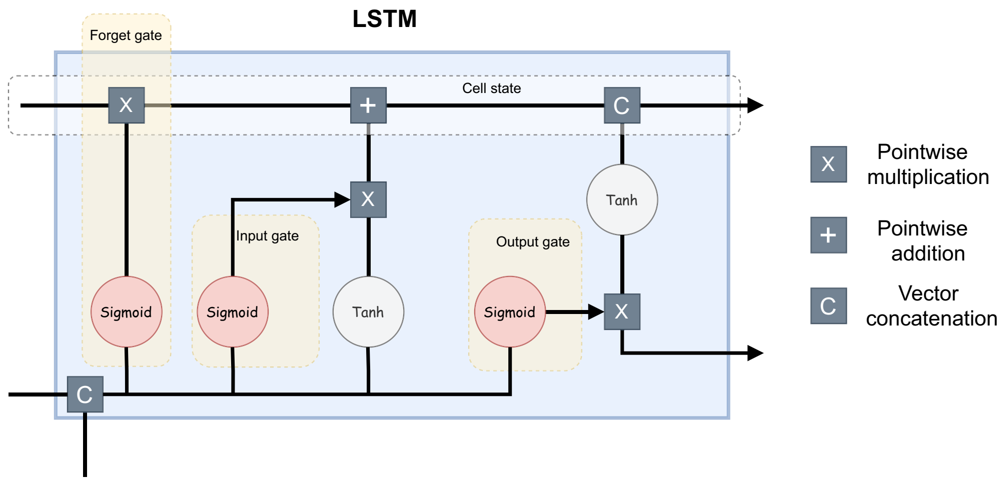

FIGURE 6 The LSTM cell structure.

3.3 | Other neural networks

Recently, Transformer models have been considered state-of-the-art models due to the high performance of these models in many applications, including bioinformatics (Shin et al., 2020), text ranking (Lin et al., 2020), machine translation (Liu, Duh, et al., 2020), and question answering (Garg et al., 2020). Transformers rely on attention mechanism instead of recurrence compared to RNNs and CNNs such as Megatron-LM (Shoeybi et al., 2019), RoBERTa (Liu et al., 2019), and T5 (Raffel et al., 2019). Thus, the Transformer model benefits from the parallelization used in the attention mechanism and the encoder and decoder layers. For instance, BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2018) is a complex network architecture that combines the Transformer-based network architecture with the attention mechanism and shows remarkable performance in many research fields, especially in language modeling. Most of the recently developed architectures are based on the Transformer-based network architecture, including the DistilBERT (Sanh et al., 2019), BART (Lewis et al., 2019), Reformer (Kitaev et al., 2020). In addition, generative models such as Deep autoencoders (Hinton & Salakhutdinov, 2006) and GANs (Generative adversarial networks) (Goodfellow et al., 2014) are used to generate synthetic data and model the data generatively. The autoencoder learns to map the input data to a latent low-dimensional representation using the encoder part. The decoder part reconstructs the input data and reverses the encoder operation. An autoencoder is a powerful tool for denoising, data compression, and dimensionality reduction. Meanwhile, GANs use two networks namely the generator and discriminator, to perform image generation (Schonfeld et al., 2020; Vahdat & Kautz, 2020), style transfer (Karras et al., 2019, 2020), adversarial training (Karras et al., 2020), or long text generation (Guo et al., 2018). The generator is used to imitate the input data distribution and generate synthetic data, while the discriminator is used to distinguish the synthetic data generated by the generator from the real data (input data).

4 | APPLICATIONS OF DL FOR 6G

In this section, we present various DL methods used to improve and boost the performance of many 6G applications, including 6G privacy and security, 6G sustainability, wireless communications, and 6G-enabled IoT.

4.1 | Applications of DL for 6G privacy and security

There are more detailed survey papers about the security and privacy issues for 6G, including some potential applications for artificial intelligence techniques such as DL methods, as presented by Kaloudi and Li (2020), Nguyen, Lin, et al. (2021), and Zhang and Zhu (2020). However, to provide the reader with sufficient data about the applications of DL techniques in different aspects of the 6G, we will summarize some applications for DL methods for 6G security and privacy.

4.1.1 | Deep learning in existing network privacy and security applications

Up to now, no pure applications for DL techniques for 6G privacy and security. Thus, we will introduce some of the applications for 5G. There are different approaches proposed in the literature for the 5G security (Ahammadi et al., 2022; Anand et al., 2021; Sicari et al., 2020) and privacy (Wang, Liang, et al., 2021; Zhu et al., 2021). Sun et al. (2021) proposed an edge-enabled distributed DL platform by dividing a general DL training network into front and back subnetworks. The front network is new to the data input, and it is separately trained at the edge of the device, where the output of the front subnetworks is sent to the back subnetworks at the cloud center. This proposed approach approved its high performance using different evaluation tests. Kim et al. (2020) studied the problem of hiding wireless communications from eavesdroppers that employ a DL classifier for the detection of the appearance of transmission of interest. The cooperative jammer (CJ) is used to transmit carefully crafted adversarial perturbations over the air to fool the eavesdroppers to classify received superposition signals as noise. Rathore et al. (2021) proposed a DL and blockchain-empowered security scheme for intelligent 5G-enabled IoT. The main idea is to use DL for intelligent data analysis operations, where blockchain is used for data security. This scheme is hierarchical, with DL and blockchain processes emerging across the four layers of cloud, fog, edge, and user. To show the framework's validity in practical applications, it is simulated and assessed using a variety of conventional measurements of latency, accuracy, and security. Mohammed et al. (2020) proposed a system for adaptively, dynamically, and holistically optimizing quality of service (QoS), energy efficiency, security, and privacy using Deep Reinforcement Learning (DRL). The model comprises two modules and is constructed on a three-layered model. The model creates rules and judgments based on critical characteristics such as data and computation offloading rates, radio channel statuses, transmit power, task priority, fog node selection for offloading, and data migration.

Qu et al. (2020) presented a generative adversarial network (GAN) enhanced location privacy protection approach for 5G networks to conceal the location and even trajectory information. They constructed a subset of data via posterior sampling, proven to meet differential privacy standards from the end device's perspective. Then, a data augmentation technique based on traditional GAN is designed to generate a series of privacy-preserving full-sized synthetic data from the central server-side. Ullah et al. (2021) developed a clone detection in Android-based 5G-IoT System. Device automation for clone detection is accomplished by selecting several components for Android source files. CFG analysis and function weighting are employed to use components further. The RNN model was applied for cloned application training and testing. The proposed scheme was tested on five different Android applications cloned and sold on various Android marketplaces. Lv et al. (2021) studied security problems existing in 5G heterogeneous networks. First, the security issues in 5G heterogeneous networks were discussed, focusing on two aspects of physical layer security issues and DL application prospects in communication technologies. After that, the interaction of DL and 5G heterogeneous networks was investigated. DL techniques, modulation information recognition, and beam creation were all combined. The use of DL in communication was examined, and DL-based modulation information recognition and beamforming were introduced. Finally, the challenges of using DL to solve security problems in 5G heterogeneous networks were discussed. Ftaimi and Mazri (2022) discussed the challenges of 5G networks security and their innovative features. They addressed the potential applications of DL methods in storage resources and management. Also, they highlight the flows of DL in security issues. Lu et al. (2019) addressed the security and privacy issues of the 5G vehicle-to-everything services. They presented a survey on existing approaches and discussed potential security, privacy, and trust attacks in 5G vehicle-to-everything. They found that DL also can have a critical role in both privacy and security. Sánchez et al. (2021), a new method called AuthCODE was proposed for privacy-preserving and multi-device continuous authentication architecture. This method aims to overcome the constraints of single-device solutions by considering additional behavioral data from heterogeneous devices. Also, the proposed method, AuthCODE, introduces a new set of features that mix user interactions with various devices. The usefulness of the capabilities was demonstrated in a genuine Smart Office scenario with numerous users interacting with their mobile devices and desktops. Several machine learning (ML) and DL classifiers were used with five datasets to assess the quality of the proposed AuthCODE.

4.1.2 | Deep learning for 6G security

Intelligence is one of the main differences between 5 g and 6G (Nguyen, Lin, et al., 2021). The advanced AI methods, including ML and DL, create innovative models for the 6G (Challita et al., 2020). The 6G network operators will adopt the advances of AI and DL to enhance their services, including security issues. The physical layer of the 6G networks is vulnerable to attacks, such as jamming and eavesdropping (Arfaoui et al., 2020; Li, Yu, et al., 2021).

Deep learning methods can be utilized to develop advanced security defense systems by improving the ability of the detection mechanisms (Erpek et al., 2018; Xie et al., 2020). Ebrahimi et al. (2021) used deep reinforcement learning (DRL) for enhancing randomness in physical layer secret vital generations. Perazzone et al. (2021) applied artificial noise (AN) based on channel state information (CSI) of the physical layer to improve the physical layer authentication. DL methods have also shown significant performance in intrusion detection systems in the network layer, as concluded by Aldweesh et al. (2020). Troia et al. (2020) implemented different methods based on deep reinforcement learning for traffic engineering in software-defined wide-area networking. Ayala-Romero et al. (2019) proposed a dynamic resource controller for the virtualization of radio access networks using deep reinforcement learning. More so, there are also various applications for the DL method such as deep neural network (DNN) for removing malicious traffic (Sengupta et al., 2020), CNN, and LSTM (Mao et al., 2018).

AI faces cybersecurity challenges (Caroline et al., 2020; Yang et al., 2020). It is also suggested by many studies that AI-based systems are also vulnerable to cyberattacks (Kaloudi & Li, 2020; Lim et al., 2020). Deep learning techniques used for different security applications, such as biometric verification systems (Edwards & Hossain, 2021; Hwang et al., 2020). There are also potential applications for DL methods for security issues in vehicular networks as described by the survey paper presented by Tang et al. (2019). There are existing DL methods proposed for network layer security applications in recent years. For example, Ferdowsi and Saad (2018) developed a DL method for discovering cyberattacks for IoT signal dynamic authentication. The proposed method authenticates the reliability of signals. Additionally, a deep reinforcement learning approach is also used to predict the state of unauthenticated IoT devices (IoTDs) and judge the IoTDs that need to be authenticated. Also, in the application layer, some existing AI-enabled security applications have been developed (Abualigah, Diabat, et al., 2021); for example, Du et al. (2017) introduced a security system, called DeepLog using LSTM. The main idea of this system is to deal with log data as a natural language sequence. Thus, DeepLog automatically learns log patterns, and it can detect anomalies when log patterns deviate from the model trained from log data under normal execution. Li et al. (2020) developed a blockchain-based data security scheme for AI applications in 6G networks. They studied indoor navigation and autonomous vehicles in the context of 6G. They evaluated the proposed blockchain-based security system using a case study of the indoor positioning system and studying the potential security issues in 6G networks. It is worth mentioning that blockchain may play an essential role in 6G security (Hewa et al., 2020). Li et al. (2020) developed a blockchain-based data security scheme for AI applications in 6G networks. They studied indoor navigation and autonomous vehicles in the context of 6G. They evaluated the proposed blockchain-based security system using a case study of the indoor positioning system and studying the potential security issues in 6G networks. Catak et al. (2021) presented a mitigation approach for adversarial attacks against 6G ML-based methods for the millimeter-wave (mmWave) beam prediction using adversarial learning. In this method, the main idea is to generate adversarial attacks against machine learning systems for producing faulty results by manipulating trained DL methods for 6G security applications. Table 3 summarizes some previous studies presented for 6G security based on DL models.

4.1.3 | Deep learning for 6G privacy

Similar to the previous generation, the privacy of the 6G is also another critical issue that has received wide attention (Mistry et al., 2021; Porambage et al., 2021). As defined by Sun et al. (2020), privacy means the ability of individuals or groups to seclude and express themselves, or their information selectively, especially for individuals." Privacy violations happen daily due to the rapid development of AI applications and the widespread of smart devices and ubiquitous wireless networks. As reported by Datoo (2018), every day, more than seven million pieces of data are leaked. The blooming of AI methods, including traditional ML and more advanced DL methods, which leverage large data to improve system efficiency and learn and produce models to make choices, is one of the greatest drivers of privacy concerns in 6G. Furthermore, the 6G structure is likely to survive a lot of data interchange and ubiquitous smart applications (Strinati et al., 2019), and datasets, including private information, are at risk both in the terminal and throughout the connection process. Thus, data privacy is a critical issue that needs more investigation (Wang, 2019; Zhang, Liang, & Niyato, 2019). There are many applications for ML and DL methods to protect privacy in literature. For example, Yang, Wang, et al. (2019) proposed a new biometric template protection method based on a binary decision diagram for DL-based finger-vein biometric systems. This method can

TABLE 3 Summary of works on deep learning for 6G and security.

Reference	DL technique	Application/focus	Contribution/benefits
Perazzone et al. (2021)	Artificial noise based on CSI	Physical layer authentication	Used AN based on channel state information to improve physical layer authentication
Aldweesh et al. (2020)	Deep Learning	Intrusion Detection	Demonstrated the performance of DL methods in intrusion detection systems at the network layer
Troia et al. (2020)	Deep reinforcement learning	Traffic engineering	Implemented various DL-based methods for traffic engineering in software-defined wide-area networking
Ayala-Romero et al. (2019)	Deep reinforcement learning	Resource control	Proposed a dynamic resource controller for radio access network virtualization using DL
Edwards and Hossain (2021); Hwang et al. (2020)	Deep learning	Biometric verification	Discussed the use of DL in biometric verification systems
Tang et al. (2019)	Deep learning	Vehicular networks	Explored potential DL applications for security issues in vehicular networks
Ferdowsi and Saad (2018)	Deep learning	IoT signal authentication	Developed a DL method for discovering cyberattacks in IoT signal authentication
Abualigah, Diabat, et al. (2021)	N/A	Application layer security	Introduced AI-enabled security applications, such as DeepLog using LSTM, for security at the application layer
Li et al. (2020)	Blockchain	Data security	Proposed a blockchain-based data security scheme for AI applications in 6G networks
Catak et al. (2021)	Adversarial learning	Adversarial attacks	Presented a mitigation approach for adversarial attacks against 6G ML-based methods, particularly for mmWave beam prediction

create a non-invertible version of the original finger-vein template. Ma et al. (2019) proposed a combined method for Android malware detection using DNN. They built a 2-class classification scheme that detects whether the incoming applications are malicious. Li, Sun, et al. (2018) developed a malware detection system, called Significant Permission IDentification (SigPID) using the SVM classifier. This system is based on permission usage analysis to deal with the huge increase in Android malware. There are also many studies that present different applications for Android malware detection using different ML and DL methods, such as CNN (Hsien-De Huang & Kao, 2018; Wang et al., 2019), and LSTM (Fu et al., 2021; Sung et al., 2020). Table 4 lists some previous DL-based models suggested for 6G privacy.

As noticed from the aforementioned studies, almost all of the privacy and security developed models were for the existing network systems. The 6G will be built on the existing infrastructure of the 5 G networks, so some of the developed models may be further developed to fit the newer 6G systems. We summarize that the privacy and security of the 6G need more investigation, especially by using the recent advances in DL technologies.

TABLE 4 Summary of works on deep learning for 6G privacy.

Reference	DL technique	Application/ focus	Contribution/benefits
Yang, Wang, et al. (2019)	Binary decision diagram	Finger-vein biometric systems	Proposed a template protection method for DL-based finger-vein biometric systems to enhance privacy
Ma et al. (2019)	DNN	Android malware detection	Developed a 2-class classification scheme for detecting malicious Android applications using DNN
Li, Sun, et al. (2018)	SVM	Android malware detection	Introduced SigPID, a malware detection system based on SVM and permission usage analysis
Wang et al. (2019); Hsien-De Huang and Kao (2018)	CNN	Android malware detection	Utilized CNN for effective Android malware detection
Fu et al. (2021); Sung et al. (2020)	LSTM	Android malware detection	Employed LSTM for detecting Android malware

4.2 | Applications of DL for 6G sustainability

The 6G networks should promote global sustainability because it is seamless connectivity and support for a wide range of services; as well as it also should minimize energy consumption and produce zero waste when different resources are interconnected. Therefore, 6G should improve environmental sustainability by consuming low-energy technologies, low emissions, and pollution prevention. The relevant features of the DL techniques led the researchers to use them to produce a powerful solution in order to improve and apply the 6G in different fields within the air, terrestrial, and underwater communication (Bhat & Alqahtani, 2021; Imoize et al., 2021).

In this trend, four scenarios were proposed by Yrjölä et al. (2020) for the 6G business. They also proposed 16 alternative future scenarios considering the key trends, related uncertainties, and interactions. The scenarios include sustainability, business, geopolitics, and user experience, whereas these discussions include societal, economic, and environmental perspectives. The conclusion of the study highlighted the importance of a sustainable future that considers the security and privacy issues in all fields, including business, government, community, and different communication types such as air, terrestrial, and underwater communication. It also highlighted the importance of bringing relevant stakeholders to help solve sustainability issues in the ecosystem. In the same efforts, the sustainability of 6G for the IoT in terms of security was also considered by Iwendi et al. (2021); they proposed a DL method to detect cyber-attacks using an LSTM classifier. The model was evaluated and compared to some of the state-of-the-art methods. The experiment results showed the effectiveness of the method with an accuracy of 99%.

Moreover, Vrind et al. (2020) introduced a model called aerial asset manager (AAM) for Low Altitude Platform (LAP) deployment as well as four infrastructure architectures for aerial infrastructure sharing. For traffic forecasting, the model applied a DL model, namely LSTM. This model aims to help plan the deployment and sharing of LAPs within different operators. The experimental results showed that the AAM model obtained some results such as 96% accuracy in data traffic forecasting, 45% reduction in the LAP fleet, and about 53% improvement in LAP resource utilization compared to previous works. Furthermore, Spyridis et al. (2021) applied a DL method to support the IoT infrastructures of 6G. In this context, the DL method tried to lead some unmanned aerial vehicles (UAV) to the mobile sensor's unknown location by using a graph convolutional network architecture to cluster the network of unmanned aerial vehicles (UAVs); the number of the cluster was dynamically selected by a heuristic algorithm whereas, the partitions were defined by optimizing a loss function of received signal strength indicator. The experiment results showed that the method could cluster the UAVs and remove those out of covering by returning them to the base. Besides, the method outperformed the previous works in the required time needed to reach the target.

The study of Mao et al. (2021) focused on improving the performance of satellite UAV severed 6G IoT. The study provided key 6G techniques, namely energy harvesting, THz, ML, and edge computing. The ML technique-based deep learning was utilized to solve computation offloading problems. The LSTM model was applied to address this task. The experimental results showed the effectiveness of the DL model and improved the performance of the system computation rate and task success ratio. In addition, Fadlullah and Kato (2020) proposed a DL model using the CNN algorithm with an asynchronous update regarding the content experience. The authors used the aerial and terrestrial model (HCP) to predict mobile users' distribution and traffic flow. The HCP applied the cooperative communication of the user equipment and heterogeneous base stations to predict the content caching placement. The HCP was evaluated using two datasets containing 100,000 ratings and over a million ratings, respectively. The results showed the effectiveness of the HCP method as well as it obtained a higher accuracy (80%) (Iwendi et al., 2021).

On the other hand, a model-based internet of underwater things was presented by Vegni et al. (2021) using a footprinting localization algorithm and wireless signals to support 6G networks. Their method followed three stages: constricting the experiment database, detecting likely positions, and estimating the position. They applied the model to different water types and clear ocean water types. The results showed that the model worked efficiently when the database was updated correctly to reflect the type of water. In Table 5, we highlight some previous studies for 6G sustainability based on DL.

4.3 | Applications of DL for green 6G

We expect 6G will be born with inherent traits, given the aggressive pursuit of a greener, smarter to strengthen 6G. Therefore, one of the most basic design criteria for the 6G in the industry's long-term development is "green." DL techniques promise to address energy efficiency, connectivity, and QoS issues in the green 6G future. DL, Reinforcement Learning (RL), and Federated Learning (FL) may be used to build and optimize 6G architecture and network orchestration cost-effectively. In addition, DL might reduce the complexity of the network for 6G network construction. DL has become increasingly far-reaching and vital in energy savings due to the many 6G enabling applications, such as autonomous cars, smart cities, smart homes, smart grid, smart healthcare, and industrial automation (Al Shinwan et al., 2022; Zhao et al., 2022). Table 6 highlights some of the previous studies on green 6G.

4.3.1 | Energy efficiency

The energy-saving cells and their compensating cells may be dynamically recognized using wireless big data acquired from the network. Then, real-time cell traffic, resource usage, and other data may be adequately anticipated by using

TABLE 5 Summary of works on DL applications for 6G sustainability.

Reference	DL technique	Application/focus	Contribution/benefits
Vrind et al. (2020)	LSTM	Aerial asset management	Introduced the AAM model for LAP deployment with traffic forecasting using LSTM, improving resource utilization
Spyridis et al. (2021)	Graph convolutional network	UAV clustering	Proposed a DL-based method to cluster UAVs for mobile sensor location, outperforming previous works
Mao et al. (2021)	LSTM	Satellite UAV networks	Applied DL to offloading strategy, improving task success ratio and system computation rate in 6G IoT
Fadlullah and Kato (2020)	CNN	Mobile user distribution prediction	Presented the HCP model for predicting mobile users' distribution and traffic flow, achieving higher accuracy
Vegni et al. (2021)	Footprinting localization algorithm	Internet of underwater things	Introduced a model-based internet of underwater things using wireless signals and localization algorithms, demonstrating efficiency in different water types

TABLE 6 DL for green 6G (summary).

Reference	DL technique	Highlighted	Benefits of technique
Iwendi et al. (2021)	LSTM	Intrusion detection system, internet of things	Detect cyberattacks on a networking system
Vrind et al. (2020)	AAM + LSTM	Traffic forecasting	Capacity enhancement, maximizes the resource utilization of the LAPs
Spyridis et al. (2021)	GCN	IoT, UAV, clustering, RSSI	Saving energy, trace an RF-emitting node
Mao et al. (2021)	LSTM	Satellite networks, wireless-powered IoT devices edge computing, cloud computing, Offloading	AI-based offloading strategy improves task success ratio and system computation rate
Fadlullah and Kato (2020)	CNN	collaborative caching, edge computing, UAV, heterogeneous computing platform, terrestrial base stations, federated learning	Facilitating the desired edge intelligence in the 6G tiny cell

DL techniques. The users in the energy-savings cell will be moved to the compensation cell when the energy-savings cell is in a state of low traffic load, putting the energy-savings cell to sleep. Simultaneously, real-time prediction and monitoring may bring up dormant energy savings cells in time for peak traffic. Simultaneously, dormant energy savings cells may be woken up in time for peak traffic through real-time prediction and monitoring, maximizing user experience while decreasing network resource/power usage (Lei et al., 2013).

4.3.2 | Connectivity and QoS

Machine-to-machine (M2M) connection refers to communication between machines that does not require human interaction (Dawy et al., 2017; Zhou, Chang, et al., 2021). Thus, these robots or gadgets would be connected, collecting data from their surroundings and sharing it and people securely. For example, health sensors gather data and safely deliver end-to-end devices to the cloud by utilizing communication between apps and server environments. A doctor can access smoothly to patient data in the cloud (Thota et al., 2018). Furthermore, as described in Alsamhi and Lee (2020) and Alsamhi, Lee, Guizani, et al. (2021) blockchain and DL enable safeguard data collection by drones and robots during disease outbreaks. RL (Challita et al., 2018; El Haber et al., 2021) was developed for connecting drones and to trade-off the minimal latency and optimize the connection with energy efficiency.

Drones have recently emerged that may help improve connection and provide data in real-time (Alsamhi, Afghah, Sahal, et al., 2021). Also, the incorporation of drones as airborne base stations was crucial to the development of 6G. The drone has many benefits over smart environments, including dynamic deployment, inexpensive deployment costs, improved channel conditions due to Line of Sight (LoS), spectrum efficiency, and so on (Alsamhi et al., 2019; Gupta et al., 2020). Drones can act as base stations, relay stations, and data collectors (Almalki et al., 2021). Drone data gathering in various sectors can replace many IoT devices, including agriculture, mining operations, military, and industrial services. Drone flight paths must be optimized using intelligent self-organization approaches. The authors of Alsamhi et al. (2021b) used ANN to optimize drone location and trajectory depending on signal intensity. The drone can follow people's behavior or smart devices to gather data from anywhere at any time and any distance. ML methods will be used to examine the collected data. Drones are employed for gathering data quickly due to the limitations of drone flying, such as limited battery lifetime (Mozaffari et al., 2017). The authors proposed the DNN in Zeggada and Melgani (2016) for the classification of the image captured by drone. This study does not look at the usage of machine learning in the context of drone communicating wirelessly with one another or with IoT devices on the ground. However, this is taken into account by the writers in Chen, Mozaffari, et al. (2017). This study used RL methods to determine the link between each user's data rate and the drone's position. The best drone sites are predicted using user content and mobility request distribution. In Banafaa, Özgümüş, et al. (2022), connected UAVs have been proposed in future wireless networks. The authors focused on the challenges of UAV, including 3D implementations, channel modeling, performance evaluation, and power efficiency. In addition, authors in Angjo et al. (2021) introduced an overview of the handover management for connected drones in future mobile networks. The study explains how current research approaches drone-related problems, paying particular attention to the handover process. As well as this work also offers a broad overview of drone integration in heterogeneous networks and explores particular solutions to potential issues.

Nonetheless, the problems of improving mobile edge computing are minimizing end-to-end latency and reducing energy usage. As a result, sophisticated approaches are required for mobile edge caching and compute prediction. To this aim, machine learning may be used to forecast mobility patterns and the distribution of users' content requests. By grouping users with similar interests and storing preferred items, ML may forecast computing job needs and predict users' interests. As a result, network devices can improve connection and reduce global latency by anticipating job computing needs and user preferences. In addition, machine learning-based clustering techniques may efficiently categorize consumers based on their interests and content requests. The authors introduced ANN to calculate cache replacement in Cobb and ElAarag (2008) and Romano and ElAarag (2011). However, the Hadoop platform is used to create the prediction of content popularity (Baştuğ et al., 2015).

The studies (Alsharif et al., 2016; Fathollahi & Kasturi, 2016) use ANN to discuss IoT device connection and wireless communication. In this case, ANN is critical for improving driver behavior modeling (Morton et al., 2017), categorizing things (Fathollahi & Kasturi, 2016; Rausch et al., 2017), and predicting mobility speed (Alsharif et al., 2016). The IoT also covers the growing popularity of entities and things that use unique IDs to autonomously send data over a network. Sensors, computer devices, V2V, M2M, buildings, smart grids, home automation, and smart wearable devices play a vital role in the growth of IoT communication (Park & Kang, 2015).

Identifying IoT devices based on signal attributes, communication channel characteristics, and logical traffic features has been the subject of several studies. For example, in Pekar et al. (2020), authors developed a technique for detecting rogue smart devices and reconnecting the victim device to the network during a disaster, as it was deceived (Saruhan, 2007). Additionally, the authors of Gu et al. (2008) and Strayer et al. (2008) proposed approaches for clustering botnet-related network traffic patterns, where device connection patterns and exchanged data are detected. Machine learning is also utilized to detect malware based on network traffic characteristics (Bekerman et al., 2015; Kouliaridis & Kambourakis, 2021). In Meidan et al. (2017), the authors present ML for IoT device detection and identification based on network data, asserting that ML can help identify various network node types. They used data from various devices and network traffic interactions to identify IoT devices, drones, and robotics. In addition to the work in Meidan et al. (2017), authors in Mahalle et al. (2013) employed machine learning to identify IoT devices based on their energy consumption, categorizing them into two categories: low and high energy-consuming devices. Moreover, in Stöber et al. (2013), a combination of k-means and SVM was proposed to detect smartphone fingerprinting based on application activity. The focus was on smartphone characteristic categorization, and they calculated the time required for device identification. Lastly, in Al-qaness et al. (2023) and Zander et al. (2005), machine learning techniques were used to classify applications and traffic.

Different communication technologies must currently collaborate for end-to-end QoS provisioning in complicated network and application settings. This includes humans, objects, and robots communicating with each other and the data center. IoT device interaction is becoming a complex problem, and enhancing QoS in IoT networks is crucial for the success of IoT applications (Nurelmadina et al., 2021). While the QoS approaches and parameters are described (Alsamhi & Rajput, 2014a), improving QoS plays a critical role in ensuring the delivery of services. Communication, data collection, and storage should all be considered due to the exponential proliferation of IoT devices. As a result, the study in Yousefpour et al. (2017) suggests the use of an IoT fog cloud, which is essential for meeting IoT service latency and QoS requirements. The utilization of machine learning approaches for IP traffic categorization in IP traffic networking to enhance QoS was discussed in Nguyen and Armitage (2008). However, this study focuses solely on the IP traffic network and does not mention the use of machine learning to improve the QoS of IoT devices. Furthermore, several research studies, such as Alsamhi et al. (2021), have addressed machine learning approaches to improve QoS (Chen et al., 2022).

The relevance of applying ML approaches in sensor routing, and energy-aware routing for improving QoS is discussed in Barbancho et al. (2007)). The authors of Luo, Liu, et al. (2016) discussed QoS prediction for Industrial IoT (IIoT) using Kernel ML. It also looks at the parallels and connections between QoS data and its counterparts. The combination of ML with IoT devices will improve QoS and create smart, intelligent, and efficient things. As demonstrated in Kraemer et al. (2017), ML can efficiently manage and operate sensors, with optimizing ML approaches playing a role in balancing the needed energy consumption and data rate of sensors.

IoT cloud enables things to communicate at any time, from anywhere. The connectivity capabilities of many autonomous IoT devices are projected to expand considerably as objects link in the IoT cloud. If a large number of IoT devices contact the channel at the same time, congestion may occur during the channel access phase, resulting in substantial delay (Hasan et al., 2013). As a result, many solutions for regulating the random-access channel load have been presented (Hassanpour & Ghasemi, 2016; Koseoglu, 2017). The majority of this research is based on channel access probability. On the other hand, DL was proposed by Kim and Kim (2017) to accomplish IoT efficient load-balancing.

To minimize the cloud's communication traffic burden and computing strain, DL has been introduced for vehicle platoon control, heterogeneous data processing, predicting driver behavior, path planning, and security (Ali et al., 2021; Chen, Mozaffari, et al., 2017). DNN is ANN with several hidden layers, each of which will train dependent on the hidden levels before it (Chen, Challita, et al., 2017). It is appropriate for recognizing and implementing the complicated model's characteristics using huge information obtained from smart city IoT devices. Furthermore, it has made substantial advancements in various research domains, including big data, IoT, and voice recognition (Chen, Challita, et al., 2017). The LSTM technique is one of the most extensive DNN algorithms for sequence classification (Graves et al., 2013).

In Balaji and Lavanya (2018), the authors gave an overview of DL methods and applications in the IoT. CNNs, autoencoders, limited Boltzmann, and sparse coding are the four types of DL approaches. Image captioning, visual tracking, and object detection are examples of IoT applications that can benefit from these approaches. Furthermore, because DL methods may learn hidden layer characteristics, they are more critical than other AI techniques (LeCun et al., 2015).

Based on YOLOv3, the authors of Cao et al. (2021) redesigned the CNN network structure and loss algorithms. The finding showed that the proposed approach allowed the model to fully learn the labeled information from all datasets. The authors of Chen et al. (2021) presented a Credit Reinforce Byzantine Fault Tolerance (CRBFT) consensus mechanism using RL. The CRBFT algorithm splits nodes into three categories, each with different responsibilities: sub-nodes, master nodes, and candidate nodes, and assigns credit to each. Experiment results demonstrated that the CRBFT algorithm could significantly increase the security of a consensus network. Furthermore, this decrease in the consensus network was beneficial to saving energy and lowering pollutants.

Due to the 6G scale, density and heterogeneity would make modeling dynamic and complex 6G networks using the same methods unfeasible. Deep learning will play a vital role in optimizing future 6G networks (Zhang, Liang, & Niyato, 2019). Through continuous learning and model adaption, AI will specifically address difficulties related to optimal resource use and support for various QoS/QoE needs. To allow large-scale deployment of 6G networks, this will justify a demand for the creation of new network designs and system models, as well as protocols, standardized interfaces, and data formats (Lin & Zhao, 2020). Network resource demands produced by big IoT installations may be addressed with AI-based predictive resource allocation algorithms that focus on challenges like unpredictable network access and latency. Ali et al. (2019), for example, look at the predictive resource allocation technique, in which base stations offer network access to devices proactively, reducing collisions and latency. Reinforcement learning methods are frequently used to tackle adaptive network access scheduling issues, in which decisions are made based on a large state-action space that encompasses a wide range of channel circumstances and traffic characteristics. Deep reinforcement learning uses neural networks as a function approximator to learn rewards in a feedback loop between a decision-maker and a physical system, allowing the decision-maker to repeatedly adjust its behavior depending on the input from the system. Adaptive modulation, coding scheme selection, power selection, and beamforming (Ali et al., 2020) are just a few of the fields where deep reinforcement learning algorithms have been used. Summary: QoS, security, flexibility, and even intelligence will all be increasingly demanding and diverse in 6G, all of which will provide a challenge to improving energy efficiency. Furthermore, the dynamic energy harvesting method, widely used in 6G, makes power control and network management much more difficult. DL has been generally recognized as the sole option to handle these difficulties and eliminate human intervention. In many communication settings, academia and industry have performed substantial research to reduce energy consumption, manage energy harvesting, and increase energy efficiency. Table 7 summaries the applications of DL for green 6G.

4.4 | Application of DL for wireless communication

The growing demand for new solutions is recognized and with the predicted technological development over the next decade (Jameel et al., 2020), it is already possible to visualize the need to relocate beyond 5G and design a new structure integrating the innovative system to meet new needs at both the individual social level (Strinati et al., 2019). An overview of 6G Wireless communications is given (Huang, Hu, et al., 2020; Zhao, 2019), including the hardware

TABLE 7 DL for green 6G (summary).

Reference	DL technique	Highlighted	Benefits of technique
Zhou et al. (2020)	DNN	Drone location, energy cost, task information	Delay
Kim (2017)	RL	QoS optimizations	Responding IoT and being suitable for enhancing QoS in wireless communication operations
Barbancho et al. (2007)	SOM and NN	Energy consumption and delay	An accurate method to route data through the network
Bernard and Nakib (2017)	Bayesian	Battery charge and transmission power	Obtaining energy-efficient for green IoT
Yang, Alphones, et al. (2019)	DQN	Channel quality and status with QoS	Energy efficiency and channel assignment
Luo, Liu, et al. (2016)	KLMS	Industry IoT and web service QoS	Predict QoS values for the industrial IoT
Barbancho et al. (2007)	SOM and NN	Energy consumption and delay	An accurate method to route data through the network
Wang et al., 2016	ML	QoS-aware traffic	Traffic classification framework of different kinds of networks
Sharma et al. (2019)	DNN	Channel gains and the status of battery	Throughput energy efficiency
Alsamhi et al. (2021)	ML	Connectivity and QoS in smart environments	Energy efficiency, QoS, Reliable connectivity
Santur et al., 2017	DL	Improve QoS and reduce process time in smart cities	Management IoTs constitute information resources in smart cities
Luo, Lv, et al. (2016)	ANN	IoT network tracking efficiency	Tracking accuracy
Yang and Xie (2019)	AC	Power and spectrum management, traffic load and channel SNR	Throughput, delay and transmission rate
Gopi et al. (2021)	K-means	Adaptive modulation for drone communication networks	QoS, coverage area, avoid interference
Du et al. (2018)	CNN	IoT network image detection accuracy	The accuracy of detecting image
He et al. (2019)	Q L	Harvested energy of cognitive radio networks	Energy efficiency optimization
Stöber et al., 2013	KNN/SVM	Traffic applications and activities	Network traffic
Huang, Ma, et al. (2020)	CNN	Link reliability of wireless senor networks	Routing optimization
Alsamhi et al. (2018), Alsamhi, Almalki, Al-Dois, et al. (2021)	ANN	Drones signal strength and trajectory	Energy efficiency and QoS

architectures that may be used to reconfigure such surfaces and the potential and problems of developing enabled wireless communications in various applications. These applications are given as follows.

4.4.1 | Mobile applications

On the 5G of mobile communications (Shafin et al., 2020), it is time to start thinking about a new generation like the 6G. With a 10-year from concept to reality, it is now essential to think about the sixth mobile communications (Lu & Zheng, 2020). In Zhang, Liang, and Niyato (2019), 6G visions are presented to cover the road for the development of 6G and beyond. The latest 5G technologies are studied, and the importance of further research into 6G is highlighted. Terahertz (THz) communications, in particular, may be utilized to enable mobile ultra-broadband, symbiotic radio, and satellite-assisted communications can be used to accomplish super IoT, and machine learning techniques are potential AI prospects (Yan et al., 2020). The fundamental concept, significant problems, and state-of-the-art techniques are given, as solutions for each technology.

To tackle the joint time-slot scheduling problem, sub-band scheduling and power allocation systems are presented in this paper (Yu et al., 2020). This problem is an NP-complete mixed-integer nonlinear program (MINLP) problem. A greedy shrinkage algorithm (GSA) is used to achieve a sub-optimal solution to decrease computing complexity. Simulations are used to prove the proposed method's efficacy. According to the results, the suggested system may produce a 12.5%–60.7% throughput improvement compared to existing methods. 6G will go beyond mobile Broadband and will be necessary to offer ubiquitous AI services from the network's core to the network's end devices. Furthermore, AI will be crucial in developing and optimizing 6G infrastructures, protocols, and operations. In this paper (Letaief et al., 2019), 6G technologies are studied that might allow mobile AI applications and Intelligence 6G network design and optimization techniques. There will also be a discussion of hot topics in the development of 6G.

Mobile edge computing (MEC) for intelligent IoT is explored in this paper (Zhao et al., 2020), where many users have some intellectual duties that are helped by various computational access points. The system performance may be enhanced by offloading some activities to the CAPs, which reduces latency and energy consumption, which are two significant parameters in mobile computing networks. The suggested DL-based technique may considerably lower the system's latency and energy usage.

4.4.2 | Detection-based applications

A new deep learning structure is needed for large grant-free arbitrary entrance in 6G communication over the IoT channels (Lu, 2019; Peneti et al., 2021).

Based on the idea of approximation message passing in Qiang et al. (2020), a model-driven deep learning method for joint action detection and channel model is suggested. Also, four critical parameters, not the entire method design, must be learned for this algorithm. Furthermore, it does not need previous knowledge of active probability and channel variance, and it can considerably enhance performance with a small quantity of training data. A simulation study confirms the suggested deep learning algorithm's efficacy.

The linear and nonlinear attributes obtained from 5G-enabled healthcare IoT create a time-frequency power spectrum from HRV sequences (Zhang et al., 2021). A DL model based on a hybrid of a deep CNN and a LSTM network is used to categorize normal sinus intervals, and arrhythmia periods are used to organize normal sinus periods and arrhythmia periods. Using a tenfold cross-validation method, this model's average accuracy, sensitivity, and precision were 99.06%, 98.29%, and 99.73%, respectively. The combined CNN-LSTM model can reliably identify arrhythmia and has potential clinical promise.

By allowing artificial intelligence in low latency communication, giving a new approach for constructing wireless networks (Salh et al., 2021). This is accomplished by using big data to learn, forecast, and make decisions about a stream of individuals. The research paper's secondary objective is to improve a multi-level design. This paper expanded on several research gaps among DL and 6G that are currently unknown.

4.4.3 | Sensing-based applications

Compared to typical wireless networks (Katz et al., 2019), the data in IoT and 6G wireless networks grows substantially with greater dimensions (Hmedoush et al., 2022; Zhang & Wang, 2020). In this paper (Liang et al., 2021), a convolution-based transfer reduced sensing model based on transfer learning is presented to reconstruct the reduced signal. The suggested technique is evaluated using an ultra-wideband radar echo signal and the Mnist hand-written dataset. Under various noise levels, sensor numbers, and signal sparsities, the suggested model outperforms existing recovery methods in 6G-IoT.

A DL-based NN method is utilized to reduce interfering signals by capturing the properties through DL (He et al., 2020). An iterative detection approach of a traditional symbol-by-symbol detector is used. User scheduling improves system detection accuracy, and many user selection criteria are provided to select a particular best user among many. Finally, simulation results demonstrate an ultra-reliable accuracy rate for 5G/B5G-enabled IoT.

This paper proposed a new hierarchical 6G IoT network including UAVs in the sky and an intelligent, reflecting surface (IRS) (Qi et al., 2021). The system uses backscattering communication (BackCom) to transfer data in a free-ride fashion. IRS improves the distance and performance of the BackCom by increasing the energy of the reflectable signal by beamforming. The simulation results show that our technique improves the overall efficiency significantly and has a significant benefit over previous alternatives.

The architectures of centralized and distributed automation IoT networks are discussed in Song et al. (2020). Critical technological issues such as random access and spectrum sensing for various network designs are examined. DL-based methods are presented, and neural network-based methodologies are used to efficiently implement DRL system processes, including spectrum access and spectrum sensing. The many forms of neural networks utilized to conduct DRL in IoT connections are also explored.

Cognitive radio networks (CRNs) have developed viable ways to allocate the necessary spectrum to customers in an intelligent way as a result of the rising scarcity of spectrum for this equipment. Utilizing a potent CNN classifier (Perumal & Nagarajan, 2022), the compressive sensing-based cyclo-stationary feature detection approach is used to determine whether or not PU activity is present. The ideal detection has been redesigned to reduce the potential of mistakes while improving detection probability and MSE. The suggested design's sensing conductivity and accuracy have been raised to 98.5%. Superior performance has been claimed when performance measures are compared to benchmark techniques.

Future development of the next generation of automated communications equipment will be supported by the innovative platforms provided by the five generations of automation and communication systems (Alzaidi et al., 2022). If ML and optimal cell clustering are applied to the scenario, M2M data may be used to allocate resources more effectively. This heterogeneity enables the ML to maximize efficiency by making the most excellent use possible of the M2M network's remaining resources. The most challenging barrier to wireless communication during the past few years has been the lack of a radio frequency spectrum. This has happened because so many high-frequency gadgets require so much bandwidth. To handle this increased demand, cognitive radio networks have been developed.

Based on DL compressed sensing (Tong et al., 2022), this research suggested a two-step orthogonal matching pursuit technique to estimate channel state information. A composite convolution kernel function is made specifically for the first-step OMP's purpose of a rough estimation of the angles of arrivals/departures (AoAs/AoDs) from the correlation matrix. To denoise the correlation coefficient and precisely estimate AoAs/AoDs, the second-step OMP presents a Squeeze-and-Excitation Residual network (SE-Resnet) with Noise2Void (N2V) learning method. Without labeled data, the suggested technique is still functional. According to simulation, the two-step OMP considerably beats cutting-edge mmWave channel estimation techniques.

4.4.4 | Image-based applications

Low-dose computed tomography (CT) can detect lung nodules, which can help forecast the risk of getting cancer in the future. An embedded deep learning method is proposed in Wang, Liu, et al. (2020). To begin, CT scans are normalized using image clipping, standardization, and classification, and positive samples are enlarged to equalize the amount of positive and negative examples. This type features an anti-interference capability that is immediately apparent. It is reliable and accurate in detecting lung nodules; therefore, it will be helpful for early screening.

Image data mining is a hot topic in the IoT domain. An image data mining method is proposed based on the relevant feedback KNN (Ye & Su, 2021). The fundamental feature extraction analysis for picture color and shape is the objective of this paper. The improved KNN method may increase picture feature extraction efficiency, with the most excellent accuracy reaching 99.3%. The research findings can be used as a scientific reference for further research into the KNN algorithm.

4.4.5 | Network architecture and communication

Edge clouds were created to address this problem by bringing the cloud nearer to IoT devices (Kato et al., 2020). AI is a vital tool for this architecture's intelligent coordination. The purpose of this paper is to introduce such a computer architecture from the standpoint of IoT systems (Wu, 2020). It then looks at the most cutting-edge concepts for IoT cloud-edge orchestration driven by AI. Finally, a list of possible challenging issues and open topics are presented and explored, which may be valuable resources for future study in this field.

This paper discussed how to use data-driven supervised DL in URLLC, and some of the approaches' extraordinary challenges (She et al., 2020). A multi-level architecture is designed for URLLC, allowing device, edge, and cloud intelligence to handle these tremendous challenges. The central concept is to analyze latency and dependability when training NN using theoretical models and real-world data.

This paper introduces a novel DL framework for the infrared-visible cross-modal person in 6G-enabled IoT called local alignment deep network, which may satisfy all-day and real-time monitoring needs (Liu & Zhang, 2020). The suggested local alignment deep network (LADN) is optimized from beginning to finish by integrating multiple cross-modality losses. The used approach is tested on two typical standard datasets, and the findings showed that the proposed method is effective.

Iterative signal processing techniques are proposed based on DL to meet the physical layer needs for 6G networks (Jagannath et al., 2021). In the perspective of 6G networks, the shortcomings of classical algorithmic concepts and data-hungry DL methods are described. The interaction between domain expertise and DL is detailed for deep unfolded signal processing. The specificity of the next-generation cellular networks is expressly positioned in the perspective of the deep unfolded methods described in this paper. This paper inspires open research issues for future 6G networks to actualize equipment edge intelligence.

Two centricities and eight key performance indicators are described, followed by a discussion of enabling technologies to meet the key performance. A 6G structure is suggested in Gui et al. (2020) as an embedded device of enabling technologies, and four large city application scenarios are used to illustrate it. Following that, potential obstacles in developing 6G technology are explored as possible solutions. Finally, the possibilities for investigating 6G are examined to direct future studies. An overview of these studies is given in Table 8.

4.4.6 | Vehicles-based applications

Connected autonomous driving (CAV) is a crucial vertical for 6G (Lovén et al., 2019), with enormous promise for increasing road safety and road and energy efficiency.

This paper looked at 6G-enabled cooperative driving (Chen et al., 2020), a more advanced driving mode that involves exchanging information and coordinating driving. First, the 6G vehicle delay upper limits are measured using hybrid transmission and channel access methods in vehicle-to-vehicle (V2V) communications. For the rapid computation of the latency boundaries in real-time processes, a DL-based NN was created and trained. Then, for coordinated autonomous vehicles, an intelligent method is devised to regulate the inter-vehicle spacing. A Markov Chain-based approach is also suggested for predicting the parameters of system behavior, as well as a safe distance mapping method for smooth vehicle speed adjustments. According to test findings, the presented algorithms are

TABLE 8 Application of DL for network architecture and communication (summary).

Reference	DL technique	Highlighted	Benefits of technique
Kato et al. (2020)	Advanced machine learning technique	Computation efficiency is addressed	Current research on intelligent networking still has a long way to go to realize the automatically-configured
Wu (2020)	Computing architecture of IoT	Provide resources for carrying out future research	Gave potential research challenges and open issues
She et al. (2020)	Deep transfer learning	A multi-level architecture device intelligence	Each mobile edge computing server is limited
Liu and Zhang (2020)	Local alignment deep network	Local alignment technique to align features	Demonstrate the effectiveness of local alignment deep network
Jagannath et al. (2021)	Deep learning with deep unfolding	Evolving communication systems	Outline the deficiencies of the traditional algorithmic principles

effective and resilient with secure and stable cooperative autonomous driving, which substantially improves traffic safety, capability, and effectiveness.

A new DL-based lightweight AMC technique with smaller model sizes and quicker computational speed is proposed in Wang, Yang, et al. (2020). In CNN, a scaling factor is added for each neuron, and compressive sensing is used to enforce the sparsity of the scaling factors. It can aid in identifying superfluous neurons, which are then pruned. According to the results obtained, the suggested approach efficiently reduces model sizes and accelerates computing with just a little performance loss.

4.4.7 | Social recommendations-based applications

Social recommendation-based applications are expected to be a key use case for 6G networks. With the increased bandwidth and low latency offered by 6G, it will be possible to build more sophisticated and accurate recommendation systems that can take into account a wide range of social and contextual factors (Pattnaik et al., 2022).

The basic technique for ambiguity-aware social recommendation (SR) is suggested in Guo, Yu, et al. (2021) as a deep learning-based graph neural network model incorporated in the model. This solution solves the choice ambiguity problem in SR by providing adequate online data sensing and management. Two real-world datasets are chosen as experimental cases to assess the efficiency of the suggested IoT-SR. Three different measures evaluate the technique, with five standard methods serving as benchmarks. According to the empirical results, the suggested IoT-SR outperforms the benchmark techniques by at least 10% and has high resilience.

Mukherjee et al. (2021) proposed a social Internet of Things (SIoT) ecosystem designed to manage emergency services and large-scale social gatherings. For the SIoT scenario, a layered message transfer framework has been provided. Through flying ad hoc network design, the network connection is established. An opportunistic routing technique is combined with the conventional IoT message transmission protocol and implemented within a 6G software-defined network (SDN) slice. Seven distinct network slices are used for the various services and corresponding access. According to the study, a dense network scenario with opportunistic message transfer displays about 99% message delivery rate with a latency upper constraint of 2300 ms for QoS 2. Additionally, it displays 97% network coverage and 95% bandwidth utilization per slice for SDN.

In Ahmed et al. (2022), a modified resource recommendation and scheduling propagation analysis technique has been proposed. This technique depends on Federated Learning (FL) which uses the analysis of the user-log records. These logs are assessed using the bandwidth ratio of 6G to calculate the availability of resources.

4.5 | Application of DL for 6G-enabled IoT

In this section, we will review some of the studies related to applying DL algorithms in the 6G-enabled IoT. Table 9 summarizes the reviewed studies. Wang, Liu, et al. (2020) proposed a framework based on several deep learning networks with a fusion mechanism for lung nodules detection with low-dose CT to minimize the false positive rate. The feature extraction phase was performed using a CNN, residual network, and LSTM on the CT images, respectively. The authors used the ECLAP Lung Image Database[1] which consists of low-dose CT scans of 50 human data gathered in the International Early Lung Cancer Program (I-ELCAP). The extracted features from the CNN and residual network are fed into the LSTM layer, where the final feature vector is the concatenated output from each LSTM layer. The proposed framework will be used in a real-time system for lung nodules detection in the 6G-enabled Internet of Medical Things (IoMT) to provide fast medical records sharing with low delay and significant bandwidth, online monitoring, and reliable online diagnosis. In providing emergency medical treatment, 6G communication technology can provide the necessary bandwidth and delay to enable efficient treatment delivery compared to 5G and other technologies.

Liu and Zhang (2020) proposed a real-time all-day surveillance system based on 6G communication technology in a 6G-enabled IoT. The proposed system named local alignment deep network (LADN) used to link IVCM ReID (infrared-visible cross-modal person re-identification) with 6G-enabled IoT. The LADN framework employs deep learning to extract local features from the IVCM images related to pedestrians' pose variation and viewpoint variations. LADN is trained to jointly capture local and global features using a novel loss termed LAT (local alignment triplet). The LAT

TABLE 9 Application of DL for 6G-enabled IoT (summary).

Reference	DL technique	Highlighted	Benefits of technique
Wang, Liu, et al. (2020)	Fusion of CNN and LSTM features	Lung nodules detection using CT images	Minimize false positive rate
Liu and Zhang (2020)	LADN	Surveillance system using IVCM ReID	Real-time, novel loss termed LAT
Chen et al. (2020)	DNN + Markov Chain	Information sharing for CAV and V2V	Improved resource allocation inter-vehicle distance
Qiang et al. (2020)	DNN + AMP	JADCE	Few training data short-packet communications
Shao et al. (2020)	DNN + Bernoulli–Gaussian mixture distribution	JADCE	Reduce the computational resources
Shao et al. (2021)	FAT-DL	JADCE + adaptive learning strategy	Enhance the noise precision
Li, Liu, et al. (2021)	DRLR + GA + A3C	Design a routing policy for the UAVs	Maximize the coverage ratio minimize the cost of employment
Lin et al. (2021)	Dynamic nested neural network MDP + ACDRA	Dynamic real-time resource allocation	Enhance the efficiency of task execution Minimize the decision delay time

function aligns the local features during the optimization process. The proposed LADN framework was validated on two datasets namely SYSU-MM01 dataset (Wu et al., 2017) and RegDB dataset (Liu, Tan, & Zhou, 2020).

Chen et al. (2020) use the AirSim autonomous driving platform to simulate a connected autonomous driving (CAV) scenario in the 6G-enabled IoT. The authors proposed a deep learning-based algorithm for CAV in 6G-enabled IoT through information sharing and driving coordination, known as cooperative driving. Using channel access techniques, the proposed algorithm investigates the 6G V2V upper bounds communication range. The authors trained a deep learning model that consists of four layers to estimate the delay bounds in real-time and intelligent control of inter-vehicle distances. To improve the algorithm control and resource allocation further, the proposed algorithm predicts the system state parameters using a Markov Chain-based algorithm and uses a safe distance mapping method to control vehicular speed.

Qiang et al. (2020) proposed a deep learning-based framework to provide grant-free random access in a 6G-enabled IoT. The framework is a model-driven algorithm implemented and simulated for joint activity detection and channel estimation (JADCE). The proposed algorithm relies on the principle of approximate message passing (AMP), where they do not learn all the AMP algorithm architecture. Instead, the deep learning algorithm learns four key parameters. Thus, the proposed algorithm improves the performance of massive device detection by eliminating the need for information about channel distribution and active probabilities with only a small number of training data. Due to the large number of devices and the limited radio resources in 6G, the proposed algorithm requires long pilot sequences to be transmitted to the devices, violating the small IoT payload in terms of the required short-packet communications.

Shao et al. (2020) addressed the JADCE problems with sporadic traffic devices in a 6G-enabled IoT for massive grant-free random access to reduce the computational resources (large-scale antenna arrays) and time complexity. Their proposed DL-based JADCE framework termed DL-JADCE consists of four building blocks: a dimension reduction, a DL network, an active device detection, and a channel estimation. The core of the framework is a DL network trained to recover the state matrix of the device and adapt to channel settings. The DL network uses a designed denoiser that relies on Bernoulli–Gaussian mixture distribution to learn the density parameters of the state matrix. The state matrix is then used to adapt the channel settings where the goal of using the DL-based network with the denoiser is to shorten the length of pilot sequences.

Shao et al. (2021) proposed a DL-based framework named FAT-DL for JADCE in a 6G-enabled IoT for massive device detection focusing on feature exploitation such as the device state matrix complex distribution in low-dimensional space. The authors proposed prior-feature learning and an adaptive learning strategy to learn the distribution parameters of the state matrix of the device. The learning strategy incorporates an inner layer-by-layer and outer layer-by-layer network composed of the Expectation–maximization (EM) and back-propagation (BP) algorithm to boost the training performance and enhance the noise precision.

Li, Liu, et al. (2021) proposed a deep reinforcement learning model named DRLR for route policy in 6G-enabled IoT based on a recruitment scheme. In addition, the overall system consists of two parts responsible for data collection from the sensors and collected data routing. The system uses genetic algorithms to select vehicular collectors to maximize the coverage ratio and minimize the cost of employment. Meanwhile, the DRLR model is used to dynamically design a routing policy for UAVs, considering the route's energy conservation, training speed, and cost. The Asynchronous Advantage Actor-Critic (A3C) algorithm (Tuli et al., 2020) was used to train the DRLR network parameters. The designed system was compared to Vehicular Selection Scheme (CVSS) (Guo et al., 2017) in terms of vehicular coverage ratio where the proposed DRLR system outperforms CVSS by a large margin (14.961% approximately). Concerning the routing policy, the proposed DRLR system reduced the collection path length compared to the Common Search in Dynamic Programming (CSDP) (Nowakowski et al., 2018), the Simulated Annealing (SA) route scheme (Guo, Liu, et al., 2021), the Genetic Algorithm (GA) route scheme (Guo et al., 2017), and the Heuristic Algorithm (HA) route scheme (Shen et al., 2021) by 54.132%, 19.1%, 28.523% and 17.05%, respectively. The developed system shows a remarkable improvement in the coverage ratio and route cost in a 6G-enabled IoT environment.

Lin et al. (2021) addressed the dynamic real-time resource allocation in 6G-enabled massive IoT intending to enhance the efficiency of task execution. The proposed system uses a dynamic nested neural network to train the network parameters to optimize and adjust the model structure for dynamic resource allocation, considering the task requirements. Later, the authors combined a Markov decision process (MDP) and an AI-driven collaborative, dynamic resource allocation (ACDRA) algorithm to improve the resource hit rate and minimize the decision delay time. The proposed model can achieve a high hit rate and low decision delay time in 6G-enabled massive IoT networks with an 8% improvement on the average resource hit and about a 7% reduction of the average decision delay time. The system was compared to three state-of-the-art algorithms, including clustering-based heuristic edge resource allocation algorithm (CHERA) (Zhao et al., 2019), genetic algorithm-based resource allocation algorithm (GABRA) (Chien et al., 2019), and dynamic resource allocation method (DRAM) (Xu et al., 2018).

5 | CHALLENGES AND OPPORTUNITIES

Due to the rapid expansion, fast-growing network transfer, and emerging intelligent utilization (i.e., self-ruling driving, virtual reality), a modern, more active, more secure, and manageable network configuration is needed. Thus, this section concludes this research's challenges and future opportunities as follows:

- From the discussions mentioned earlier, it is clear that speed, no latency, and secure communications are required to help ML and AI at the edge, providing a beginning to the research area called communication ML. Advancing an action besides what has been presented in the early sections, we remark that utilizing the next generation of network communication at the edge or cloud can produce high-level concepts compared to conventional methods.
- ML and DL rules typically hold various parameters, and a large amount and high-quality data are needed to train big and complicated models. With insufficient data, the DL approach's effectiveness may yield an under-fitting problem.
- AI produces chances and difficulties to 6G network security and privacy. On the one side, many ML and DL methods have been applied to improve network protection issues, such as intrusion detection approaches and abnormal traffic discovery. However, most current research converges on the established network view. Current ML/DL structures and methods suffer different security risks.
- Conventionally, genetic programming, game theory, and optimization are used to solve different network problems. As the networks developing toward 6G frequently grow complex and dynamic, remarkable suspicions will not be realistic. Due to the number of used parameters and restrictions, it is complicated to obtain the optimum result of the expressed problems by traditional methods.
- The mobile AI model, including centralized cloud and distributed edge intelligence, is essential. The disseminated and lightweight intelligence installed at the network edge can significantly assist with ultra-low latency.
- The current researcher has employed ML or DL to wireless network problems, showing their approaches' effectiveness through simulations. Only some researchers tried to check the effectiveness of practical implementation.
- A simulator should be examined to validate the results of a particular ML or AI optimization method when utilized in a production ecosystem. Such methods can improve the effectiveness of networks.

- Usually, training data obtained from channel devices can be sparse, insufficient, deficient, or confused. Simulators can produce synthetic data to tackle these problems, increasing the usable training datasets. Nevertheless, evaluating the goodness of synthetic datasets is hard for administrators, particularly complicated problems that cannot be represented precisely.
- Federated learning is a new AI important technology. It was proposed by Google in 2016 and was initially employed to address the problem of mobile network monitor updates. The main goal is to perform effective ML among participants or computing connections under confidence, protect final data and privacy, and legal yielding.
- The versatility of vehicles directs to fast handovers across the links, attending to daily resource allocation. While the channel state and network structure may change continuously, traditional resource allocation strategies would probably require a rerun for each change, contracting large overhead. Here newly ML-based methods give a valuable mechanism for data-driven arrangements and collisions to improve vehicular network effectiveness.

6 | CONCLUSION

Artificial intelligence (AI) is assumed to shape future communication, such as the 6G. It is necessary to study the impact of the AI techniques, such as deep learning, on the future 6G. Therefore, in this study, we present a comprehensive survey of the application of deep learning techniques in the 6G technology. We summarized most published studies focusing on security, privacy, sustainability, green communication, applications, wireless networks, and challenges. We collected the published studies from databases such as the Web of Science, IEEE Explore, ScienceDirect, and others, with about 255 suitable published studies. We provide the readers with this well-categorized survey paper that covers all of the potential applications of deep learning methods for different aspects of 6G. We concluded that deep learning would have a significant role in the intelligence of the future 6G. More so, many topics need more and more investigation, such as device-to-device communication, security, and privacy, that have not been solved yet. With the rapid and continuous transformation and innovation of deep learning and other AI techniques, the 6G technology will fulfill the requirements of individuals, organizations, and industries in practice.

AUTHOR CONTRIBUTIONS

Mohamed Abd Elaziz: Data curation (equal); formal analysis (equal); investigation (equal); resources (equal); writing – original draft (equal); writing – review and editing (equal). **Mohammed A. A. Al-qaness:** Data curation (equal); formal analysis (equal); investigation (equal); project administration (equal); writing – original draft (equal); writing – review and editing (equal). **Abdelghani Dahou Dahou:** Data curation (equal); formal analysis (equal); investigation (equal); visualization (equal); writing – original draft (equal). **Saeed Hamood Alsamhi:** Data curation (equal); formal analysis (equal); validation (equal); writing – original draft (equal); writing – review and editing (equal). **Laith Abualigah:** Data curation (equal); formal analysis (equal); validation (equal); writing – original draft (equal); writing – review and editing (equal). **Rehab Ali Ibrahim:** Data curation (equal); formal analysis (equal); validation (equal); visualization (equal); writing – review and editing (equal). **Ahmed A. Ewees:** Data curation (equal); software (equal); validation (equal); visualization (equal); writing – original draft (equal).

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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This is review paper, no data.

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ENDNOTE

[1] http://www.via.cornell.edu/databases/lungdb.html

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