A Review of the Convergence of 5G/6G Architecture and Deep Learning

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Abstract—The convergence of 5G architecture and deep learning has gained a lot of research interests in both the fields of wireless communication and artificial intelligence. This is because deep learning technologies have been identified to be the potential driver of the 5G technologies, that make up the 5G architecture. Hence, there have been extensive surveys on the convergence of 5G architecture and deep learning. However, most of the existing survey papers mainly focused on how deep learning can converge with a specific 5G technology, thus, not covering the full spectrum of the 5G architecture. Although there is a recent survey paper that appears to be robust, a review of that paper shows that it is not well structured to specifically cover the convergence of deep learning and the 5G technologies. Hence, this paper provides a robust overview of the convergence of the key 5G technologies and deep learning. The challenges faced by such convergence are discussed. In addition, a brief overview of the future 6G architecture, and how it can converge with deep learning is also discussed.

Index Terms—5G, 6G, deep learning, Internet of Things, multi-access edge computing, software-defined networking, network function virtualization, massive multiple-input multiple-output (MIMO).

I. INTRODUCTION

The evolution of the 5G ultra-dense network (UDN) in the year 2020 and beyond is the realization of a mobile ecosystem capable of supporting 1000-fold increase in traffic when compared to the year 2010 level, and a 10- to 100-fold surge in data rates even at high mobility, and in dense areas [1][8]. To this end, more capacity is critically needed in the fronthaul, backhaul, and radio access network (RAN). Therefore, mobile network operators (MNO) are faced with the challenges of meeting the demands of the 5G UDN. According to the Fifth Generation Private Public Partnership (5GPP) [4] and the European Telecommunication Standard Institute (ETSI) [5], the 5G UDN is expected to address the following challenges beyond the capability of the present 4G Long Term Evolution-Advanced (LTE-A) network: higher capacity, higher data rate, lower end-to-end latency, massive device connectivity, reduced capital expenditure (CapEx), reduced operational expenditure (OpEx), and higher quality of experience (QoE) [2][3].

To address the challenges in the 5G architecture, it is believed that many emerging technologies must be combined. Technologies for providing more spectrum access and allowing for network densification and offloading are necessary [6]. Technologies for providing more spectrum includes millimeter-wave (mmWave), cognitive radio, and carrier aggregation techniques. Network densification involves the proliferation of small cells (e.g. femto cells and pico cells) to support the macro cells and micro cells already in use. Since high carrier frequencies are well suited for small cells, the mmWave technology with a good line-of-sight (LOS) will be necessary. Massive multiple-input multiple-output (MIMO) technology and beamforming must be deployed for good antenna design. For offloading, multi-access edge computing (MEC) and device-to-device technology will minimize end-to-end latency for real-time and safety-critical applications. Such applications include robotic applications for medical and industrial emergency response, vehicle-to-vehicle (V2V) communication, vehicle-to-infrastructure (V2I) communication, device-to-device (D2D) communication, augmented and virtual reality (AR/VR), social media, and online streaming [2]. Other technologies that are important for the successful emergence of the 5G architecture are software-defined networking (SDN) to separate the data plane and the user plane, network function virtualization (NFV) for the virtualization of the core network, and the interoperability of software from various vendors. Advances in optical networking such as optical switching and visible light communication (VLC) may also be able to address the capacity requirements.

The recent progress in deep learning has led to breakthroughs in solving complex problems that have defied solutions in the artificial intelligence community for decades. Deep learning is good at discovering intricate structures in high-dimensional data by extracting features in a hierarchical pattern. Many fields of science and engineering have embraced deep learning due to its unprecedented performance in dealing with big data. Deep learning has achieved excellent performance in image recognition and processing [5][11], and speech recognition [12][14]. It has performed better than conventional machine learning techniques at predicting drug molecules activities [15], analyzing particle accelerator data [16][17], reconstructing brain circuits [18], and predicting the effects of mutations in non-coding deoxyribonucleic acid (DNA) on gene expression and diseases [19][21]. In recent times, deep learning performed well in natural language processing (NLP) tasks [22], especially in topic modeling, sentiment analysis, question answering [23] and machine translation [24][25]. Deep learning has proven beyond doubt to become a source of hope for the future especially with the enormous amount of data that will be produced from the launch of the 5G architecture and the Internet of Things (IoT). A unique benefit of deep learning is that it can independently extract features from raw
data unlike traditional machine learning; thus, eliminating the need for human intervention for feature extraction. With the high rate of ongoing researches to develop better deep learning algorithms and architectures, it is obvious that deep learning is a technology that has come to stay.

Intersecting deep learning with 5G technology is justifiable. The enormous amount of data to be generated from heterogeneous networks (HetNets) in the 5G architecture will be collected from various sources such as smartphones, wearable devices, and self-driving vehicles. These data will not only be complex but also be available in diverse formats (e.g., video, text, multimedia) [26]. Hence, conventional methods in wireless communication become inadequate to handle these data. More so, deep learning will eliminate the necessity for domain expertise in processing the data. The advances in electronics have resulted in high computing power that has increased the speed of execution of deep learning algorithms. For instance, Graphics Processing Unit (GPU)-based parallel computing can enable deep learning to make good predictions within milliseconds. Moreover, some business enterprises such as Amazon and Microsoft own large cloud computing resources that are leased at affordable prices for very high computations. Therefore, computations can be done with better accuracy within a short period.

II. RELATED WORKS

The fields of artificial intelligence and wireless communication have grown independently over the years. However, researchers have begun to study the mutual benefits of intersecting both fields. Deep learning can introduce intelligence into the 5G architecture, while the heterogeneous and massive data generated from the 5G architecture will result in a research problem to improve the speed and inference of deep learning algorithms. Some survey papers sit at the intersection of both fields of artificial intelligence and wireless communication. We classify these survey papers into four categories: (A) overview of the convergence of traditional machine learning and shallow artificial neural networks (ANN) with 5G architecture and technologies (B) overview of the convergence of deep learning with the current wireless communication schemes (C) overview of the convergence of deep learning with a specific emerging 5G application/technology (D) overview of the convergence of deep learning with 5G architecture and technologies. The list of acronyms used in this paper is given in Table 1.

A. Overview of convergence of traditional machine learning and shallow artificial neural networks with 5G technologies

The authors in [27] reviewed the fundamental concepts of machine learning and proposed how it can be employed in the 5G technologies, which include cognitive radios, massive MIMOs, femto/small cells, heterogeneous networks, smart grid, energy harvesting, and device-to-device communications. The authors in [28] reviewed common machine learning algorithms in cellular networks. They further discussed how these machine learning algorithms can be used in self-organizing networks (SONs), and the metrics for preferring a machine-learning algorithm to others in SONs. The authors in [29] provided a survey for integrating machine learning and artificial learning techniques to enhance the efficiency of wireless communication in the areas of data acquisition, knowledge discovery, network planning, operation, and management of the future wireless networks. Also, the authors in [30] explored the possibilities of ANN-based solution approaches to enhancing 5G communications technology. The authors in [31] highlighted the benefits and limitations of exploiting artificial intelligence (AI) to achieve intelligent 5G networks, and also demonstrated how effective is AI in managing cellular network resources. Since this paper is more focused on the convergence of 5G architecture with deep learning, only some selected survey works on the convergence of 5G architecture with traditional machine learning and shallow artificial neural networks have been discussed.

B. Overview of convergence of deep learning and current wireless communication schemes

The authors in [32] studied physical-layer deep learning approach to address problems such as modulation recognition, radio fingerprinting and medium access control. This requires the domain expertise of wireless communication for the design of wireless systems that are spectrum-driven, i.e., that can learn the current state of the spectrum and take optimal actions. Similarly, the authors in [33] surveyed how deep learning can be leveraged to redesign the traditional communication system (for modulation recognition, channel decoding, and detection), and to replace it with a unique architecture that is dependent on an auto-encoder. The authors in [34] studied model-driven deep learning approaches in physical layer communications. Model-driven deep learning combines domain knowledge in wireless communication with deep learning to reduce the demands for computing resources and to lessen training time. The authors in [35] categorized deep learning applications in the physical layer of wireless communication into systems with or without block structures. The authors in [36] gave a comprehensive survey of the applications of deep learning algorithms to different wireless network layers, which includes modulation/coding in the physical layer, access control/resource allocation in the data link layer, path search, and traffic balancing in the routing layer.

C. Overview of the convergence of deep learning and a specific emerging 5G technology / application

The authors in [37] gave a holistic overview of integrating multi-access edge computing with the emerging 5G technologies. The authors in [38] surveyed comprehensively the convergence of edge computing with deep learning. They conveyed the idea of edge intelligence and intelligence edge which is derived from such convergence. Edge intelligence refers to the application of deep learning to edge nodes, while intelligent edges are the final goal of making smart devices seamlessly communicate with an intelligent edge. The work in [39] holistically investigated the technical spectrum covering the convergence of deep learning and edge computing in terms
of five enablers. Other notable work that sits at the intersection of deep learning and multi-access edge computing is found in [39–41]. The authors in [39, 40] provided an overview of the architectures, frameworks, and technologies for deep learning model training and inference at the network edge. The authors in [41] gave an overview of federated learning in mobile edge computing. In federated learning, the user devices train a machine learning model with their local data and send the model updates instead of the raw data to the edge server for fusion. Federated learning serves as enabling technology in mobile edge networks for training of a machine learning model in a collaborative manner, and it also enables the edge network optimization using deep learning. Federated learning helps to improve the privacy of data since the end users need not send their raw data. Also, by sending only model updates, edge bandwidth can be efficiently used. Recent works on federated learning integrates differential privacy techniques for enhanced privacy [42].

The authors in [26] presented an overview and a brief tutorial on deep learning in mobile big data analytics and discussed how to use Apache Spark as a scalable learning framework. Also, the authors in [43] provided a summary of the current deep learning architectures and algorithms used in network traffic control systems. The authors in [44] surveyed how deep learning can be applied from diverse perspectives to empower IoT applications in four representative domains, which are smart healthcare, smart home, smart transportation, and smart industry. Similarly, the authors in [45] surveyed how deep learning methods can be used to develop enhanced security for IoT systems. The authors in [46] summarized major reported research attempts that leveraged deep learning in the IoT domain. The authors in [47] surveyed how deep learning can be integrated with massive MIMO.

D. Overview of the convergence of deep learning and 5G architecture and technologies

The authors of [48–49] discussed the convergence of deep reinforcement learning and the 5G technologies. In our opinion, the most comprehensive survey article involving the intersection of deep learning with 5G architecture and technologies is [50]. This survey provided a very comprehensive review of mobile and wireless networking research from the deep learning perspectives and categorized them by their different domains.

All the aforementioned existing survey articles that sit at the intersection of artificial intelligence and 5G architecture have their shortcomings. The articles in category A did not apply deep learning techniques. The articles in category B are more focused on how deep learning techniques can be applied to today’s wireless communication systems, with less emphasis on the emerging 5G network. The articles in category C are streamlined to how deep learning can enhance a specific 5G technology/application. Therefore, they neglected other 5G technologies where deep learning approaches are also applicable. References [48, 49] in category D are focused only on a specific type of deep learning technique - deep reinforcement learning. Reference [50] is not well structured to specifically cover the 5G architecture and its technologies. More so, it does not cover a recent deep learning algorithm - capsule networks. Table 2 presents a comparison of existing survey papers.

Therefore, this paper specifically surveys the convergence of 5G architecture and deep learning. It starts by reviewing both the 5G architecture and deep learning architecture independently and includes capsule networks that are not present in any of the previous survey works. Then, it discusses notable research works that converge deep learning techniques with the 5G architecture, while covering the key 5G technologies. Also, it discusses the challenges posed by such convergence. Lastly, it briefly reviews the 6G architecture and discusses how the 6G architecture can converge with deep learning.

Thus, the rest of this paper is divided as follows: Section III discusses the 5G architecture and applications, Section IV discusses the deep learning architectures, Section V discusses the application of deep learning in the 5G architecture, Section VI discusses the potential challenges that may be faced by integrating 5G architecture with deep learning, Section VII discusses how deep learning can drive the future 6G technologies, and lastly, Section VIII is the conclusion.

III. 5G ARCHITECTURE AND APPLICATIONS

In this section, we briefly discuss the requirements for 5G architecture. Also, we highlight the 5G technologies.

A. 5G architecture

The 5G architecture will consist of the radio network and the cloud network [3]. The radio network covers the deployment of a UDN which includes the small, micro, pico, and femto cells [51]. This means that the 5G UDN will suffer co-channel interference, which will gradually render obsolete the current air interface. Therefore, advanced access technology such as Beam Division Multiple Access (BDMA), nonorthogonal multiple access (NOMA), sparse coded multiple access (SCMA), and Filter Bank multi-carrier (FBMC) multiple access must be employed to increase spectral efficiency. Massive MIMO must be used to increase network coverage by relying on its beam-forming gains. Advanced modulation and coding schemes, such as 256-quadrature amplitude modulation (QAM) and low parity density check codes (LDPC), can also increase spectral efficiency and be combined with massive MIMO to increase network capacity. Efficient spectrum management through cognitive radio, and the usage of the higher frequency band for mmWave communication will provide the necessary bandwidth requirements [52]. The cloud network consists of offloading techniques such as MEC, fog computing, and cloud computing. MEC and fog computing will free up the cloud space and reduce end-to-end latency in time-critical applications such as AR/VR. Cloud-RAN will allow for the aggregation of tasks and resource pooling, thus, giving rise to efficient use of network resources [53]. The decoupling of the user plane and the control plane by software-defined networking can further make small cells flexible and easily deployable. This will allow for seamless interoperability among different network providers. Also, it will allow for efficient
This paper surveyed the literature on various IoT applications that leveraged deep learning. A limitation of the paper is that it did not cover deep learning techniques which are the major drivers of 5G technologies.

This paper overviewed common machine learning techniques used in self-organizing cellular networks. This paper is limited to cellular networks only and did not cover deep learning techniques.

This paper surveyed how artificial intelligence can be applied to boost the performance of wireless network operations. A limitation of the paper is that it did not discuss deep learning techniques.

This paper explored the potentials of artificial intelligence-based solutions for 5G technologies. The survey is very limited.

This paper highlighted the benefits and limitations of exploiting artificial intelligence to achieve intelligent 5G networks. This paper is limited to cellular networks and focused mainly on machine learning techniques.

This paper discussed the need for deep learning at the physical layer and summarized the current state-of-the-art deep learning-based physical layer architecture. There is a very limited discussion on the 5G architecture.

This paper comprehensively overviewed deep learning-based physical layer processing. A discussion on using autoencoders to redesign the conventional communication system was presented. However, there was no discussion on the 5G architecture.

This paper discussed model-driven deep learning approaches in physical layer communication. The paper is limited to the current wireless communication system.

This paper overviewed recent advancements in deep learning-based physical layer communication. There was no discussion on the 5G architecture.

This paper comprehensively surveyed the application of deep learning in the current network layers. The paper discussed ten unsolved problems in this area of research. The paper majorly focused on the current physical layer architecture alone.

This paper presented a brief overview on deep learning in mobile big data analytics. It also discussed how to use Apache Spark as a scalable framework. However, it focused mainly on big data.

This paper holistically overviewed multi-access edge computing and how deep learning techniques could be leveraged. The paper is not well-structured to cover deep learning techniques. More so, it is limited to multi-access edge computing.

This paper comprehensively overviewed deep learning applications in multi-access edge computing. The concepts of edge intelligence and intelligent edge were thoroughly discussed. However, the survey work is limited to multi-access edge computing only.

This paper surveyed edge intelligence and presented a deep learning model towards training and inference at the network edge. The paper is limited to edge intelligence and does not cover other 5G technologies.

This paper overviewed applications where deep learning is used at network edge, and approaches to speed up deep learning inference across network devices, edge servers and the cloud. The paper is limited to edge computing only.

This paper reviewed the applications and challenges of federated learning in large-scale and complex mobile edge computing. The paper is limited to mobile edge computing only.

This paper overviewed the state-of-the-art deep learning architectures and algorithms used in network traffic control. The paper is limited to network traffic control only.

This paper surveyed the literature on various IoT applications that leveraged deep learning. This paper is limited to IoT only.

This paper comprehensively surveyed machine learning and deep learning techniques that enhanced security in IoT systems. This paper covered only IoT systems and excluded other 5G technologies.

This paper summarized major research works that leveraged deep learning in the IoT domain. It also surveyed deep learning approaches that support IoT applications in the fog and cloud center. The survey work is limited to IoT applications only.

This paper discussed deep learning-based techniques for modeling and estimation of massive MIMO channels. The paper is focused on massive MIMO only.

This paper reviewed deep reinforcement learning applications in communications and networking. It covered the 5G networks but did not discuss other deep learning applications.

The paper overviewed the concepts of deep reinforcement learning and reviewed its application to various challenges in 5G networks. The paper is limited to deep reinforcement learning only.

This paper presented an encyclopedic survey that sits at the intersection of wireless and mobile communication and deep learning. The paper is not laser-focused on 5G networks, and hence not very well-structured.

This paper laser focuses on the intersection of major 5G technologies with deep learning. A brief overview of the convergence of 6G architecture with deep learning is also discussed.
energy management, and to minimize over-provisioning and under-utilization of the resource. NFV will virtualize hardware operations through software applications, thus, allowing for flexibility and interoperability of network devices. In addition, local offload through D2D communications can further increase network throughput [7]. Other technologies such as VLC and optical fiber communication will also be included in the 5G architecture. Figure 1 is an illustration of the 5G architecture.

### B. 5G applications

There are varieties of emerging applications that are expected to be the major driver behind the commercial deployment of the 5G architecture. Such applications will be beneficial to a wide range of public and private sectors, which includes among others, energy, agriculture, infrastructure, health care, manufacturing, and transport. We briefly discuss the emerging applications of the 5G architecture below.

1) **device-to-device (D2D) communication:** The proliferation of wireless devices may cause wireless congestion at the small cells (base stations). D2D communication allows for a local offload without traversing the small cells [55].

2) **machine-to-machine (M2M) communication:** It is expected for the 5G technologies to introduce intelligence to lots of machines. Vehicles will be intelligent enough to communicate among themselves. Interference management schemes and the mmWave technology that provides a large bandwidth will be the driver of the M2M communication [55].

3) **Internet of Things (IoT):** IoT includes "anything" to the "anytime" and "anywhere" promises of 5G architecture. The IoT application will produce big data that will be difficult to manage. Latency, energy efficiency, and interference are possible challenges. Technologies in the 5G architecture to overcome these challenges will be mobile edge computing, cloud computing, and fog computing.

4) **Smart infrastructure:** Smart infrastructure includes smart homes, smart grids, intelligent transportation, and smart cities. The 5G RAN and cognitive radio technologies promise to satisfy the requirements for a smart infrastructure.

5) **Intelligent healthcare:** Launching of the 5G architecture will allow for robotic applications that will monitor patients’ health and records in real-time. Communication with patients and drug prescriptions will be done with minimal human intervention.

Other applications are wearable devices, smart industries, the internet of vehicles (IoVs), smart banking, gaming, and social media, etc.

### IV. DEEP LEARNING ARCHITECTURES

Deep learning is a representative-based learning technique where a cascade of multiple layers of nonlinear processing units extract features. The lower layers of the deep learning architecture learn simple features, while higher layers learn complex features, thus forming a hierarchical and powerful feature representation. Deep learning approaches can be categorized into supervised, semi-supervised or partially supervised, unsupervised and the deep reinforcement learning (DRL). Convolutional neural networks (CNN), recurrent neural networks (RNN), and recursive neural networks (CNN) are the supervised deep learning methods. Autoencoders and restricted Boltzmann machines (RBM) are unsupervised deep learning methods. Generative Adversarial Network (GAN) is the semi-supervised deep learning method. Deep Q-learning (DQL) is the deep reinforcement learning method. Deep learning techniques are deep neural networks (DNNs), with multiple layers of neurons lying between the input and the output.

Deep learning has produced state-of-the-art results in many application domains, such as computer vision, speech recognition, NLP [22, 56]. The increasing interest in deep learning is due to the availability of high computing power caused by advances in solid-state electronics, the availability of huge training data which will further increase as 5G technologies evolve, and the power and flexibility of learning intermediate representations [57].

#### A. Convolutional Neural Network

The structure of the CNN is inspired by the neurons in animal and human brains. The three main advantages of CNN over shallow neural networks are parameter sharing, sparse interactions, and equivalent representations. Computational complexity is reduced by parameter sharing because local connections and shared weights are used, leading to the training of fewer parameters. The CNN architecture is such that each layer of the network transforms one volume of activations to another using a differentiable function. The architecture consists of three main layers which are the convolutional layer, the pooling layer, and the fully connected layer.

Suppose the input data consist of pixels of dimension $W_1 \times H_1 \times D_1$ and convolved with a filter of size $F \times F \times D_1$, where the number of strides is $S$ and the number of zero padding is $Z$. Suppose there are $K$ numbers of such filters. After the filters have scan a local portion of the input image, the obtained feature map will be of dimension $W_2 \times H_2 \times D_2$, where $W_2 = ((W_1 - F + 2Z)/S) + 1$, $H_2 = ((H_1 - F + 2Z)/S) + 1$ and $D_2 = K$. For a max pool layer that comes after the first convolutional layer, the output will be of dimension $W_3 \times H_3 \times D_3$, where $W_3 = ((W_2 - F)/S) + 1$, $H_3 = ((H_2 - F)/S) + 1$ and $D_3 = D_2$. There are usually many convolutional and max pool layers before the fully connected layers. The fully connected layers are hidden layers for the high-level abstraction of the images and each has the same dimension as the previous layer ahead of it. The softmax-output layer is used for classification in supervised learning. Discarding pooling layers are important in many deep learning architectures such as capsule networks, variational autoencoders (VAEs), and generative adversarial networks (GANs). Future deep learning architectures will most likely not contain any pooling layers.

CNN has been widely used to obtain good performance in different applications such as NLP, speech recognition, computer vision [58], and post-translational modification in proteins [59], to name a few. Several architectures in the field of convolutional neural networks has been given a name such as LeNet [60], AlexNet [8], ZFNet [61] and GoogLeNet [11].
B. Capsule Networks

The capsule network (capsnet) is an improvement to the CNN, where the orientation of a 3D object is captured for proper classification [62, 63]. In the capsule network, there is a pose relationship between the simple features of lower layers that make up a higher layer feature. This is referred to as equivariance. CNN does not possess equivariance, hence it cannot correctly identify a 3D object as same if pictured from different angles. The capsule network uses a dynamic routing algorithm for routing the input vector from lower layers to the higher layer with a similar representation. A nonlinear squash function is applied to the output vector to keep the length of the vector as a probability and preserve the orientation of the vector. The dynamic routing algorithm is shown in Algorithm 1.

Algorithm 1 shows how the input vector $\hat{u}_{ij}$ of each capsule $i$ in layer $l$ is been routed to the capsule $j$ in the higher layer $l+1$ to produce an output vector $v_j$. The parameter $b_{ij}$ is initialized to zero, so that there can be a uniform distribution representing maximum randomness through the softmax function. The squash function is given as

$$\text{squash}(s_j) = \frac{||s_j||^2}{1 + ||s_j||^2} \cdot \frac{s_j}{||s_j||}. \quad (1)$$

The symbol $|| \cdot ||$ represents the $L−2$ norm. The loss function $L_c$ for capsnet is different from the popular cross-entropy loss function used in CNN, and it is given as

$$L_c = T_c \max(0, m^+ - ||v_c||)^2 + \lambda (1-T_c) \max(0, ||v_c||^2 - m^-)^2. \quad (2)$$

Since that capsnet is a deep supervised learning architecture, the parameter $T_c$ is 1 when the output of the capsnet correctly matches the label and 0 otherwise. Also, the parameter $m^+$ is commonly fixed at 0.9, and $m^-$ is commonly fixed at 0.1.

The capsnet has been successfully used for feature extraction of $28 \times 28$ pixels MNIST dataset with less training parameters than CNN [64].

C. Recurrent Neural Network

Recurrent Neural Network (RNN) is popular for processing sequential information. It is thought of as multiple copies of the same network, each network passing an information to a successor. The length of its time steps is determined by the length of the input. Unlike the feedforward neural network, where different parameters are used at different layers, RNN shares the same parameters across all time steps. It performs the same task at each step with different inputs; thus, reducing the total number of parameters for training. At each time step, the hidden layer vector $h_t$ and the output $y_t$ is computed mathematically as follows:

$$h_t = f(w_h x_t + w_h h_{t−1} + b_h) \quad (3)$$

$$y_t = g(w_y h_t + b_y) \quad (4)$$
where $x_t$ is the input vector at time $t$, $h_t$ is the hidden layer vector at time $t$, and $y_t$ is the output vector at time $t$. The parameters $w_{ij}$ and $u_{ij}$ are the weight vectors, and $b_i$ and $b_j$ are the biases. Also $f$ and $g$ are the activation functions which may be the $\tanh$ and the $\text{softmax}$ functions respectively. The main issue with the RNN is its sensitivity to both vanishing and exploding gradients [65]. Exploding gradient is not much of a serious problem because the exploding gradients can be clipped at a particular threshold. However, the vanishing gradient tends to be a more serious problem that affects long-term dependencies in RNN. RNN is widely used for sentiment classification [66] and machine translation [67] in NLP. There are special types of RNN such as the bidirectional and deep bidirectional RNN which is based on the idea that the output at each time-step may depend not only on the previous elements but also on the next elements for sentence classification. To overcome the problem of vanishing gradient, the long-short term memory neural network (LSTM), which is also another special version of the RNN was developed [68, 69]. A simplified model of the LSTM is the gated recurrent unit (GRU) [70].

D. Recursive Neural Network

Recursive Neural Network (RecNN) is seen as a generalization of the recurrent neural network that can make predictions in a hierarchical or tree-like structure, as well as classify the outputs using compositional vectors. It generates the parent structure in a bottom-up manner, and it is commonly used for sentence classification in sentiment analysis [71].

E. Autoencoders

The autoencoder (AE) is used for unsupervised deep learning with efficient data encoding and decoding. It has three layers, namely the input layer, the hidden layer, and the output layer. Its operation consists of the encoding phase and the decoding phase. In the encoding phase, the input vector is mapped to a lower-dimensional features space in the hidden layer by an encoding function. This approach is repeated until the desired feature dimensional space is reached, resulting in lossy compression. In the decoding phase, a decoding function reconstructs the original input vector from the lower-dimensional features. Thus, the autoencoder is used for dimensionality reduction, compression, and fusion.

A special type of autoencoder is the denoising autoencoder (DAE). In the DAE, the input vector is stochastically corrupted and the goal is to denoise the corrupted input vector. That is, to minimize a denoising reconstruction error. Thus, the DAE forces the hidden layer to learn more robust features and prevents it from simply learning and replicating a noiseless input vector [72].

Variational autoencoder (VAE), unlike traditional autoencoders, performs well in generative processes. This is because the encoder of a VAE outputs Gaussian distribution, which is an approximation of a posterior distribution, rather than a single point like in a traditional autoencoder. Thus, the output of the encoder of a VAE is said to be continuous. A latent variable is sampled from this distribution. More so, a VAE minimizes not only the reconstruction loss but also the Kullback-Leibler divergence between the probability distribution from the encoder and the normal distribution. This way, a VAE can cluster similar objects together and still maintain completeness [73, 74]. The loss function of a VAE is given as

$$l_i(\theta, \phi) = -E_{z \sim q_{\phi}(z|x_i)}[\log p_{\theta}(x_i|z)] + KL(q_{\phi}(z|x_i)||p(z))]$$

(5)

where $l_i(\theta, \phi)$ is the loss function of the $i$-th datapoint $x_i$. The latent variable is $z$; $\theta$ are the weights and biases of the encoder, while $\phi$ are the weights and biases of the decoder. The expected negative log-likelihood of the $i$-th datapoint in the first part of the loss function represents the reconstruction loss, while the Kullback-Leibler divergence represents the regularization.

F. Restricted Boltzmann Machines

Restricted Boltzmann machine (RBM) is a generative shallow neural network that can learn a probability distribution over a set of input [75]. When stacked together and fine-tuned with gradient descent and backpropagation algorithm, they form a deep belief network [76]. The RBM can be used for dimensionality reduction, collaborative filtering, topic modeling, and feature learning. Although RBM falls into the class of deep unsupervised learning, it can be trained to perform classification in supervised learning. The RBM has only two layers, namely the visible layer and hidden layer, whose nodes are connected across each other in a symmetric bipartite fashion. There is no connection among the nodes in either the visible layer or the hidden layer. Unlike an autoencoder, the RBM has two biases which are the input bias and the hidden bias. The goal of the RBM is to minimize the reconstruction loss and the Kullback-Leibler divergence. In recent times, RBMs have been replaced with VAEs and GANs.

G. Generative Adversarial Network

The GAN consists of two neural networks, the generator model and the discriminator model. The generator model
maps from a latent space with noise to a fake distribution of interest. The generator model aims at successfully deceiving the discriminator, whose goal is to distinguish between the generated fake distribution and the true distribution from a known dataset. Thus, the discriminator acts as a classifier. The weights and biases of both the generator and discriminator are trained with the backpropagation algorithm. Typically, the generator is a deconvolutional neural network, whose pooling layer is replaced with an upsampling layer, and the discriminator is a convolutional neural network. The adversarial nature of GAN forms a game setting where both the generator and the discriminator are trying to reach a Nash equilibrium in a two-layer minimax game. This is represented as

$$\min_G \max_D V(D, G) = \min_G \max_D \mathbb{E}_{x \sim p_{\text{data}}(x)} \left[ \log D(x) \right] + \mathbb{E}_{z \sim p_z(z)} \left[ \log (1 - D(G(z))) \right]$$

(6)

where \(V(D, G)\) is the value function; \(D\) represents the discriminator; \(G\) represents the generator; \(p_z(z)\) is the prior of the input noise (latent) variable; \(D(x)\) represents the probability that \(x\) came from the true distribution \(p_{\text{data}}(x)\) rather than the generator’s distribution \(p_G\); and \(G(z)\) represents the fake information from the generator.

GAN was first designed by Ian Goodfellow [77], and it is said to be one of the most important (if not the most important) discoveries in the field of deep learning in the last ten years. There are many variants of the GAN such as CSGAN [78], infoGAN [79], LOGAN [80], cGAN [81] and so on. A complete survey on GAN is found in [82]. GAN has various applications such as image processing and computer vision, object recognition, video applications, natural language processing, data science, and even in the medical field. Although GAN falls into the class of deep semi-supervised learning, it can be used for classification in deep supervised learning, and can also be used in deep reinforcement learning.

H. Deep Reinforcement Learning

Deep reinforcement learning (DRL) combines reinforcement learning with deep learning to create an efficient algorithm that has wide applications in games, robotics, NLP and computer vision, etc. The DeepMind’s AlphaGo algorithm that uses a deep Q-network (DQN) and beats the human world champion of the Go game is a notable example.

The DQN uses deep neural networks to replace the Q-table of the primitive Q-learning algorithm in a higher dimensional state space [83]. The Q-learning algorithm [84], is a model-free algorithm that calculates the quality of a state-action combination, and can be derived from the Bellman optimality equation [85]. The Q-learning update rule is sequential and given as

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta (y_t - Q(s_t, a_t))$$

(7)

where \(\eta\) is the learning rate; \(s_t\) is the state at time \(t\); and \(a_t\) is the action taken at time \(t\); \(Q(s_t, a_t)\) is the Q-value of the state-action pair at time \(t\). The temporal difference target \(y_t\) can be simplified as

$$y_t = r_t + \gamma \max_a Q(s_{t+1}, a)$$

(8)

Here, \(r_t\) is the reward obtained from applying the action \(a_t\) in the state \(s_t\); and \(\gamma\) is the discount factor. The difference between \(y_t\) and \(Q(s_t, a_t)\) in (7) is the temporal difference.

The two important changes introduced to the primitive Q-learning by DQN are the experience replay memory to allow for training on a random batch of previous experiences drawn uniformly at random from the storage distribution \(U(D)\), and the target network to solve the problem of instability of the target due to its correlation with the current model estimate. This makes the DQN use two neural networks for training. The first is the Q-network with parameter \(\theta_1\) for sampling the experience replay memory at iteration \(i\), and the second is the target network with parameter \(\theta^-_1\) at iteration \(i\). The parameters from the Q-network are copied and updated to the target network every \(C\) steps in an online learning fashion.

The loss function at iteration \(i\) is given as

$$L_i(\theta_i) = \mathbb{E}_{(s, a, r, s') \sim U(D)} \left[ (y_{i}^{DQN} - Q(s, a; \theta_i))^2 \right]$$

(9)

and

$$y_{i}^{DQN} = r + \gamma \max_{a'} Q(s', a'; \theta^-_i).$$

(10)

There are other notable variations of the DQN such as the Double-DQN (DDQN) [86] and the weighted-DQN (WDQN) [87].

V. Integrating Deep Learning into 5G Architecture

Deep learning has been applied in the literature to the various technologies that make up the 5G architecture. In this section, we will review the major papers discussing the applications of deep learning to the key 5G enabling technologies. Specifically, we divide this section into the following subsections:

1) Deep learning applications to massive MIMO.
2) Deep learning applications to multi-access edge computing.
3) Deep learning applications to the Internet of Things.
4) Deep learning applications to software-defined networking and network virtualization.

A. Deep Learning Applications to Massive MIMO and mmWave

Massive MIMO and mmWave are key enabling technologies for the 5G architecture. This is due to the very high data rates and multiplexing gains promised by these technologies. These technologies require a large number of antennas and thus, large channel matrices for training. Training large channel matrices cause computational problems and coordination overhead. These have motivated the use of deep learning techniques that leveraged low-overhead features of the environment to predict massive MIMO and mmWave channels with high accuracy, and enable coordination of base stations with low complexity. However, the use of deep learning techniques for massive MIMO and mmWave technologies requires a generic dataset that can be fine-tuned for various wireless environments and channel conditions. The dataset needed for wireless settings
is complex than that for computer vision or NLP, where the dataset is fixed and need not be adjusted to meet certain conditions. The author in [83], generated a generic deepMIMO dataset from Remcon Wireless Insite Raytracing simulator [89]. The deepMIMO channels constructed from the simulator capture its dependence on the environment, and the transmitter/receiver location. The number of antennas, orthogonal frequency division multiplexing (OFDM) subcarriers, and several channel paths can be fine-tuned to be used with any supervised deep learning algorithm.

In frequency division duplexing (FDD) networks that utilize massive MIMO to perform precoding, downlink channel state information (CSI) is estimated and fed back from the user equipment (UE) to the base station causing excessive overhead. Traditional wireless communication approaches, such as codebook-based approaches, quantization vector, and compression sensing, have been proposed to reduce the feedback overhead. When the number of antennas increases, it complicates the codebook and quantization vector approaches, also when there is a model mismatch, the compression sensing approach experiences difficulty. Hence, deep learning-based approaches have been developed to mimic compression sensing, yet with better performance. The CsiNet [90] feedback network uses an autoencoder-like architecture, where the encoder obtains codewords by learning channel structures from training data, while the decoder recovers the CSI through a one-off feedforward multiplication. CsiNet-LSTM extends this method to handle time-correlation in time-varying channels. The CsiNet-LSTM [91] uses a recurrent convolutional neural network (RCNN), which combines a CNN and an RNN. The CNN extracts spatial features, while the RNN interferes correlations. Also, the authors of [92] proposed DualNet-MAG and DualNet-ABS deep learning-based feedback CSI framework that employs bi-directional channel reciprocity and limited uplink feedback for CSI estimation. In [93], the authors proposed Bi-LSTM (bi-directional LSTM) and Bi-ConvLSTM using both CNN and LSTM, to decompress and recover the CSI in single-user and multi-user scenarios in massive MIMO.

Even though dynamic time division duplexing (TDD) has been considered better than FDD for 5G UDN, it relies on conventional radio resource management schemes such as coordinated multipoint (CoMP). The challenge posed by employing conventional techniques is that they cannot cope with the unprecedented traffic envisaged in the 5G network. Although CoMP improves cell edge UE’s throughput and connection stability, it cannot assist a small cell to learn the traffic pattern in neighboring cells. More so, small cells are faced with the challenge of intelligently changing their uplink and downlink configuration before imminent congestion, to alleviate queue occupancy. Deep learning-based approaches have been proposed to introduce smartness into small cells. The authors in [94] proposed an LSTM-based approach that predicts congestion in the future based on past and present traffic data. The authors in [95] also proposed a DNN algorithm for traffic management.

Resource allocation is important in massive MIMO to deal with inter-user interference and pilot contamination. Spectral efficiency is maximized by jointly optimizing data and pilot power. The use of mathematical methods is always computationally inefficient. Deep learning can be used to approximate functions without closed-form solutions according to the universal approximation theorem [96]. The authors in [97] constructed a deep fully-connected neural network for maximizing spectral efficiency by allocating transmit power to a few users. The authors in [98] designed a DNN that uses statistical CSI to predict transmit powers in a massive MIMO system, where fading is spatially correlated. The authors in [99] developed a deep learning algorithm called PowerNet to allocate power in a massive MIMO system with a dynamically varying number of active users.

Supporting highly mobile applications such as AR poses a challenge to mmWave technology. This is because mmWave can be easily blocked by small particles as small as the size of rain droplets. Also, the frequent hand-off in UDN will introduce control overhead and latency. The authors in [100] proposed an integrated deep learning and beamforming strategy that enables high-mobile applications in large antenna array mmWave systems.

B. Deep Learning Application to Multi-Access Edge Computing

MEC is a promising technology for the 5G HetNets since it provides a reliable supplement to the cloud center. Routing data between the cloud center and end devices are faced with the challenges of latency, scalability, and privacy. MEC addresses these challenges. The proximity of edge servers to end devices decreases latency. To address the issue of scalability, MEC utilizes a hierarchical structure consisting of end devices, edge nodes, and cloud servers to provide computing resources. MEC facilitates the use of federated learning to provide privacy requirements.

Deep learning architectures are required at edge nodes and edge devices, such as smartphones and GPUs for many applications. Computer vision tasks, such as vehicle detection and surveillance video systems are processed at small cells edge servers due to the sensitive information they contain. Vigil [101], VideoEdge [102] and Amazon DeepLens [103], are examples of computer vision system being processed at the edge nodes. NLP tasks involving deep learning algorithms are processed at edge devices, such as wakewords detection in Amazon Alexa [104] and Siri [105]. In VR, deep learning is used to detect objects of interest in the field of view of users. In AR, deep learning is used to predict the field of view of users and impose on them a virtual overlay. Deep learning can be used for detecting malicious packets at the edge nodes, and also to make a real-time decision on where packets should be sent.

Offloading high computations from resource-constrained edge devices to resource-rich edge nodes deployed at the base station or roadside unit (RSU) will free up spaces in edge devices [88]. Thus, end-users will have higher QoE due to fast computations especially in gaming applications. This means that DNNs are required at the edge nodes to process such computations. The inference can be downloaded by edge devices. Edge nodes computing resources can be shared for processing offloaded DNN tasks from many edge devices.
Deep learning is also useful for in-network caching [40]. In-network caching is used to serve multiple users in the same geographical location requesting the same contents. To avoid latency and congestion of the cloud server, caching such content is required. In caching systems, deep learning is either used for content popularity prediction by supervised deep learning algorithms or to decide a caching policy using deep reinforcement learning.

There are three main methods for providing fast inference in multi-access edge computing with deep learning for high QoE. The first method is to ensure fast inference on resource-constrained edge devices executing DNNs. To improve computational speed and still maintain accuracy in resource-constrained devices, training parameters can be minimized using techniques deployed in computer vision. Such techniques include YOLO [106], MobileNets [107], Solid-State Drive (SSD) [108], and SqueezeNet [109]. Compressing the DNN model is also a viable approach, although accuracy slightly reduces. Examples of compression techniques are knowledge distillation, parameter pruning, and parameter quantization. Knowledge distillation [110] creates a smaller DNN that imitates the characteristics of a bigger DNN. Parameter pruning removes the least important parameters. Parameter quantization converts floating numbers to numbers with low-bit width. Some works combined some of these techniques such as Adadeep [111] and DeepMon [112]. High-performing processors in computer processing devices (CPUs) and GPUs, together with custom-made application-specific integrated circuits (ASICs) have made edge devices suitable for performing deep learning computations. Examples of these are Nvidia’s EGX platforms [113], Intel’s CPU, GPU, Field Programmable Gate Arrays (FPGAs) and Google’s Tensor Processing Units (TPUs) [114].

The second method to improve deep learning computational speed in multi-access edge computing is to offload tasks from edge devices to one or more edge servers. Techniques such as data pre-processing and resource pooling can be utilized. In the data pre-processing technique, redundant contents are removed before offloading to the edge servers. In resource pooling, many edge devices share the same edge server resource, thus, maximizing bandwidth efficiency. Some of the works on resource sharing are VideoStorm [115], Chameleon [116], Mainstream [117]. These works study the trade-off between latency, accuracy, and other performance metrics.

The third method involves intelligent offloading across any combination of edge devices, edge servers, and the cloud center. This method can be any of the following: binary offloading, partial offloading, or distributed offloading. Binary offloading is a decision either to offload all DNN computations or not. Recent techniques for binary offloading are DeepDecision [118] and MCDNN [119]. Partial offloading is a decision on what fraction of DNN computations is to be offloaded. Some part of the computations may be done at the edge devices before being sent over to the edge servers to reduce latency. A work using this technique is Neurosurgeon [120]. DNN computations can be shared among the edge devices, edge servers and the cloud as in DDNN [121]. In distributed offloading, DNN computational tasks can be shared among neighboring edge devices with available computing resources to avoid routing the edge servers or cloud. Examples of such techniques are DeepThings [122] and MoDNN [123].

C. Deep Learning Applications to the Internet of Things

Wireless sensors are expected to be incorporated into the IoT and programmed with intelligence to provide a wide range of applications over the Internet. Thus, the network environment becomes complicated, and communication resources become scarce. More so, IoT gateways will be faced with congestion and bandwidth challenges arising from the big data generated from ubiquitous IoT devices [124, 125].

Applying deep learning to IoT devices can enhance their sensing and prediction capabilities. The authors in [126] discussed four key research questions that need to be answered for seamless interaction between IoT and deep learning capable of meeting the demands of the 5G HetNets. The research questions are: (1) What are the deep learning architectures capable of processing and fusing sensitive input data for diversified IoT applications? (2) How can the resource consumption of deep learning models be reduced, so that they can be efficiently deployed at resource-constrained IoT devices? (3) How to guarantee confidence from the predictions of deep learning models deployed at IoT devices? (4) How to minimize the need for labeled data for deep learning prediction?

Some research works focus on answering the above-mentioned questions. A unified and customizable deep learning platform called DeepSense [127] was developed to meet the requirements of many IoT applications. The DeepIoT [128] can compress deep learning parameters, so that deep learning architectures can be deployed in resource-constrained IoT devices. RDeepSense [129] was also developed to provide reliability assurance to deep learning predictions in IoT devices. Finally, unsupervised and semi-supervised deep learning architectures such as GANs have lowered the dependence on labeled data.

It is important to note that the big data generated from the proliferation of IoT devices will be susceptible to noise, bias and some anomalies [126]. Therefore, it is expected for deep learning algorithms to provide reliable and accurate inference regardless of these. Also, deep learning architectures are expected to deal with real-time data streams requiring fast processing. An example of such IoT application is in smart cities [130]. An important aspect of smart cities is smart energy management. The authors in [131, 134] applied deep learning techniques to predict energy usage in smart cities. Traffic management in smart cities is another important area where fast processing deep learning algorithms are required [135]. Self-driving cars are embedded with numerous sensors that require deep learning algorithms with fast processing for timely decision-making [136]. Also, smart security systems at homes, and real-time image processing applications using CNN require deep learning algorithms with fast computational speed and have been discussed in [137].

A challenge to be encountered in the IoT deployment is security threats. IoT systems are prone to passive attacks such as eavesdropping, and active attacks such as spoofing, man-in-the-middle, Sybil, and malicious inputs [45]. Deep learning
algorithms have demonstrated robustness against these security threats. For instance, CNN was used to detect malware intrusion in Android devices [138]. RNN was used to detect malicious attacks in network traffic [139]. Similarly, auto-encoders were used to detect malicious attacks in network traffic [140]. A combination of auto-encoders and deep belief networks was used to detect both malware and malicious codes [141]. The authors in [142] proposed a GAN to provide security in IoT cyberspace and to detect abnormal system behavior [143].

D. Deep Learning Applications to Software Defined Networks and Network Virtualization

SDN is a network paradigm that decouples the control plane from the data plane. Thus, software-based controllers, which serve as the control plane, are logically centralized to provide network intelligence. On the other hand, network devices, which serve as the data plane, become simple packet forwarding devices easily programmable through open interfaces [143]. NFV virtualizes network functions (NFs) by shifting NFs from dedicated hardware to software-based applications running on commercial off-the-shelf equipment [144, 145]. This way, CapEx and OpEx are reduced. Deep learning has been used to address some challenges peculiar to SDN. These challenges are traffic classification, routing optimization, resource management, and security [146].

In traffic classification, the authors in [147] identified mobile applications using deep neural networks. The flow features used for training an 8-layer deep neural network were destination address, destination port, protocol type, packet size, and TTL. The authors in [148] used multi-layer perceptron (MLP), stacked AE, and CNN for real-time traffic monitoring and classification in an SDN controller. The authors in [149] proposed a novel deep learning algorithm for prospective traffic load and congestion. The deep learning architecture consists of a deep belief network and a CNN. The authors in [150] applied DRL to control multimedia traffic without any mathematical model.

In routing optimization, The authors in [151] applied DRL to optimize routing, where the goal is to optimize routing among all source-destination pairs given traffic matrix. Also, the authors in [152] proposed an LSTM-based network framework called NeuTM for predicting network traffic. They obtained real-world traffic data from the GEANT backbone network for training [153]. The authors in [154] used deep Q-learning to jointly optimize the computational capabilities of blockchain nodes and controllers. Similarly, the authors in [155] developed TDRL-RP deep Q-learning framework for deciding immediate trust path for long-term rewards in vehicular ad-hoc networks (VANETs).

In the area of resource management, the authors in [156] used DRL to optimize the joint resource allocation in software-defined virtualized VANETs. Similarly, [157] optimized joint resource allocation in smart cities. The authors in [158] used a special type of RNN called ESN for predicting the content request distribution and mobility pattern of each user; thus optimizing QoE and transmit power in cache-enabled Unmanned Aerial Vehicles (UAVs). The authors in [159] applied LSTM in the study of Service Level Agreement (SLA) in SDN. The authors in [160] proposed a DRL algorithm called DeepRM to solve the problem of packing tasks with multiple resource demands in SDN. The proposed algorithm had a fast convergence. The authors in [161, 162] applied DRL to solve resource management problems in network slicing.

In the area of security, the author in [163] used DNNs to detect network intrusion by classifying traffic flow into normal and anomaly. The SDN controller collects flow statistics from all switches and forwards them to the deep learning-based detection system. The DNN was trained with NSL-KDD datasets [164]. On detecting network intrusion, the SDN controller uses the OpenFlow protocol to adjust the switches’ flow table to avoid intrusion attacks. The authors in [165] proposed a Gated Recurrent Unit RNN (GRU - RNN) algorithm for intrusion detection in an anomaly-based intrusion detection system (IDS). The author in [166] developed a novel IDS called NDAE to speed up intrusion detection without compromising on accuracy. The author in [167] applied a combination of CNN and RNN for detecting distributed denial-of-service attacks (DDoS). The authors in [168] applied stack autoencoder for detecting DDoS in SDN environments. The training was based on the NSL-KDD dataset with five class classifications. The authors in [169] proposed ATHENA, a framework for scalable anomaly detection in SDN. ATHENA is deployable in large-scale SDN because it offers a wide range of network features and detection mechanisms. The authors in [170] applied CNN, AE, and RNN to detect anomaly-based intrusion. The training set was the NSL-KDD dataset and the test sets were NSLKDD+ and NSLKDDTest2. A comprehensive survey on the convergence of deep learning with SDN/NFV can be found in [146, 171, 172].

VI. CHALLENGES FACED BY THE CONVERGENCE OF DEEP LEARNING AND 5G TECHNOLOGIES

Converging deep learning with 5G technologies comes with its challenges. Some of the challenges are:

- Deep learning algorithms are easily fooled [173, 174]. This also includes deep reinforcement learning [175]. Attackers can distort the training data by introducing samples that will steer the deep learning algorithms towards a wrong prediction in classification problems. For instance, the authors in [176] crafted white-box and universal black-box adversarial attacks to reduce accuracy for deep learning-based radio signal classification. The authors showed how the attackers construct small powerful perturbations to distort radio signal classification.
- Deep learning algorithms are black-boxes hard to interpret [176]. This poses a challenge in wireless communication, where well-understood mathematical concepts have been developed and have stood the test of time. Also, deep learning algorithms are designed to solve a specific task such as computer vision and may perform poorly on complex tasks associated with dynamically changing wireless environments [177].
- Deep learning is heavily dependent on data. Although, this is beneficial in 5G architecture, where an enormous...
volume of data will be produced. The cost of acquiring such enormous data and processing the data with GPUs and cloud computing technologies may override the benefits. More so, the acquired data may require some expensive pre-processing techniques. For instance, the use of data processing frameworks such as Apache Spark and Hadoop, and deep learning software such as TensorFlow, Theano or PyTorch, on distributed data will incur the financial cost of GPU hardware, software, and cloud computing services [178]. Another challenge with deep learning for classification problems is that the deep learning algorithms must be trained with all possible instances of positive and negative examples. There might be a massive collection of data favoring the positive examples and an insufficient number of negative examples. Thus, the deep learning algorithm will perform poorly [179]. Although, transfer learning may be helpful.

- Hyper-parameter tuning in deep learning using cross-validation is by trial and error. There is no theoretical background to understand how to obtain the optimal tuning hyperparameters, and to assess the performance of the algorithm. In deep CNNs where the number of hyper-parameters grows at an exponential rate with the depth of the network, finding these optimal hyper-parameters is a herculean task. Although the AutoML platform tried to resolve this challenge, the solution appears to be expensive [180].

- Deep learning algorithms are liable to prediction errors. Prediction errors in wireless systems will cause strong interference and will result in high transmission collision probabilities [181]. However, deriving the prediction error probability for most deep learning algorithms is still a challenge.

- Meeting up with the latency requirement in wireless networks, and deploying deep learning platforms in wireless devices with limited memory storage for training large parameters remain a challenge. Even when regularization techniques are used, such as $L_p$ regularization, dropout, batch normalization, early stopping, and so on, DNNs still rely on large training parameters [182].

VII. BRIEF OVERVIEW OF THE FUTURE 6G ARCHITECTURE, AND ITS CONVERGENCE WITH DEEP LEARNING

The future 6G network is expected to deliver superior performance compared to the 5G network. The data rate is expected to be in multiterabytes per second (Tb/s) and the network will be super-data-driven. The 6G architecture will encapsulate ground, water, and air networks to deliver ubiquitous wireless connectivity. Some of the enablers for the launch of the future 6G architecture are supermassive MIMO (sm-MIMO) to provide unlimited wireless service and increase spectral efficiency; teraHertz (THz) communication, sub-mmWave communication, and visible light communication (VLC) to provide the critically needed frequency spectrum; holographic beamforming (HBF) for frequency reuse; large intelligent surfaces (LISs), orbital angular momentum (OAM) multiplexing, and blockchain-based spectrum sharing for dynamic spectrum management; quantum communication and computing for fast and secure networks beyond the 5G networks; molecular communications for energy-efficient communication; and internet of nano-things [183]. The vision of the 6G network is to provide full wireless coverage that supports diverse ways to interact with smart devices which includes tactile, brainwave, speech, visual, and audio communication [184]. To improve data rate, modulation schemes such as index modulation and spatial modulation will be used. The 6G network is expected to enhance the 5G network by providing enhanced mobile broadband (eMBB), ultra-reliable low latency communication (URLLC), massive machine type communication (mMTC), and ultra-low-power communication (ULPC). The key performance indices (KPI) for evaluating the 6G network will be spectrum efficiency, energy efficiency, peak, and user-experienced data rate, latency, mobility, and density of connectivity [185]. The peak data rate is expected to be at least 1 Tb/s which is a hundred times higher than the peak data rate for the 5G network. The user-experience data rate will be at least 1 Gb/s which is ten times higher than that of 5G. The latency over the air is expected to be within the range of $1 - 100 \mu s$, and total connectivity is ten times higher than that of 5G. The energy efficiency is expected to be within $10 - 100$ times higher than that of 5G networks, while the spectral efficiency will also be $5 - 10$ times higher [183, 186, 187].

The realization of the 6G architecture will be powered by advances in deep learning. Deep learning will be required for spectrum sensing in a 6G network, where spectrum sensing will occur simultaneously with a large number of devices. Deep learning will identify the characteristics of the spectrum, and sense the spectrum intelligently using the right training model. Improved data mining and analytics will be required to unearth useful information and provide knowledge from massive data generated from the 6G architecture in real-time. Deep learning techniques will be useful for selecting the optimal parameters in sub-mmWave and THz communication. Deep learning will be required to optimize energy efficiency and harvesting, especially for undersea, air, and space communication [188]. Although research work has begun on 6G networks both in the academia [189, 190] and in the industry [184], there is still a lot of open problems that must be resolved to make possible the launch of the future 6G architecture [191–193].

VIII. CONCLUSION

The emerging 5G architecture is expected to meet the demand for increased capacity and increased data rate, massive device connectivity, increased quality of experience, reduced latency, and reduced capital and operational cost. To achieve this, a combination of some state-of-the-art technologies must be commercially deployed. These technologies include massive multiple-input multiple-output technology, millimeter wave technology, multi-access edge computing, software-defined networking, network function virtualization, and the Internet-of-Things. On the other hand, deep learning has attained tremendous progress at discovering intricate
structures in high-dimensional data in the field of artificial intelligence integrating computer vision, bioinformatics, and natural language processing. This has raised some hope of a symbiotic relationship when deep learning converges with the 5G technologies.

A lot of research work sits at the intersection of both fields. Therefore, this paper surveyed the convergence of 5G architecture with deep learning. Unlike most survey papers that discussed how a specific 5G technology can converge with deep learning, this paper considers how the whole spectrum of the 5G architecture can converge with deep learning. Also, this paper is well-structured to laser-focus on the emerging 5G technologies. The potential challenges of such convergence are discussed. Lastly, this paper provides a brief overview of the future 6G architecture, and how it can converge with deep learning.

Declaration of Competing Interests
The authors declare that they have no known financial interest or personal relationships that could appear to affect the work reported in this paper.

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