<u>*Review Article*</u>

Artificial Intelligence and Machine Learning in 5G Network And Beyond: A Survey and Perspectives

Abstract

Examining successful examples, both academics and industry researchers state that artificial intelligence (AI) and 5G technology as a whole are efficient applications. Thanks to artificial intelligence, wireless communication scenarios that cannot be easily modeled have been solved more easily and the uncertainties in technology have been eliminated to a great extent. In addition, 5G technology is expected to combine communication, computing, sensing and control for various industries. Having these features at the same time raises the problem of complexity. This problem can be solved with artificial intelligence and machine learning features. Thanks to these technologies, data is protected, while meeting low latency requirements and minimizing both communication and computational burden. In this context, it is very important to examine machine learning and artificial intelligence applications that focus on optimizing communication, computation and resource allocation for 5G technology.

For this purpose, in this study, it is aimed to provide a comprehensive perspective on the state of artificial intelligence research for 5G by examining recent studies, to summarize the contributions and trends related to these technologies, and to help researchers and practitioners make informed decisions about choosing the right machine learning and artificial intelligence approach.

Keywords: 5G network, Machine Learning, Artificial intelligence

Introduction

There are also many research areas where machine learning and artificial intelligence can play a significant role and improve the quality of service in 5G and beyond networks. Machine learning applications can increase the efficiency of anomaly/error/attack detection, access control, and authorization applications. Thus, with the integration of machine learning, continuous protection is provided for legitimate communications on 5G and beyond networks.

Recently, with the widespread use of various machine learning (ML) techniques in 5G networks and mobile communications, many complex problems have been solved. Machine learning techniques can be broadly classified as supervised, unsupervised, and reinforcement learning. Supervised learning where the user works with labeled data; Among some 5G network problems, classification and regression problems predominate. Some regression problems, such as the programming of nodes and energy availability in 5G, can be predicted using Linear Regression (LR) algorithm.

Statistical Logistic Regression, bandwidth, and frequency allocation can analyze accurately. Some supervised classifiers are applied to forecast network demand and allocate network resources based on link performance; Specifies the topology setup and bitrates. Support Vector Machine (SVM) and NN-based approximation algorithms are involved in observable channel state studies. 5G technologies enable a host of new types of intelligent devices and industry digitization. AI solutions help coordinate devices, radio, and computing resources.

5G technology and artificial intelligence benefit organizations by enriching their capabilities. While 5G improves the speed and responsiveness of wireless networks, artificial intelligence shows the potential to help balance loads and increase the efficiency of devices.

Global 5G standardization enables devices and networks to work together regardless of user location and capabilities. While our life becomes more dynamic with 5G technology, various problems may occur. It is vital to examine the studies done to identify these difficulties.Rapid advances in AI dramatically improve the entire 5G ecosystem, performance, and efficiency. Also, the proliferation of 5 G-connected devices helps enable unparalleled intelligence and new improvements in AI-based learning and inference. Also, as on-device intelligence has garnered tremendous attention, the transformation of the connected, the bright edge has begun. This transformation is critical to harnessing the full potential of the future of 5G. With these expectations, these technologies have enough potential to transform any industry. Artificial intelligence and 5G offer potential solutions to these challenges with new levels of performance and efficiency. In addition, the artificial intelligence in the device benefits the overall 5G system with radio awareness that 5G can support boost system performance, including improved spectrum utilization and reduced interference. 5G provides better radio security, protection against malicious attacks, and enhanced detection. It also provides enhanced device experiences (such as power management and intelligent beam generation). As an advanced technology, 5G significantly improves the speed and accuracy of other technologies. Meanwhile, AI makes machines and systems work intelligently like humans. 5G accelerates cloud services, while artificial intelligence quickly analyzes and learns from the same data.

In addition to implementing AI and RAN (radio access network) at the core to enable intelligent network operation (e.g., improved quality of service, better efficiency, simplified deployment, and enhanced security), in-device AI can also benefit the overall 5G system. The enabling capability is radio awareness, which provides information through environmental and contextual sensing that can reduce overhead and latency. A 5G system can unlock enhanced device experiences such as less interference and spectrum utilization, smarter beamforming, and power management through radio awareness. It can provide better radio security, such as better detection and protection against malicious attacks.

Literature Review

Although there are many studies in the literature, each providing a particular value, this is a unique study that examines the latest research with its techniques and results. To fully understand the details of the studies in this field, many prestigious works of different periods are discussed in detail. Thus, it is not only to gain perspective and knowledge but also makes it possible for researchers to design their new approaches. When the recent studies on these technologies are analyzed:

Alawe et al. (2018) proposed a new machine learning-based solution to scale and deploy the 5G core network key element, Access, and Mobility Management (AMF) virtualized environment. According to the findings, using a neural network trained on the mobile network traffic dataset to estimate the user add request rate allows us estimating count the exact number of AMF samples required to process the upcoming user traffic.

Fonseca et al. (2019) concluded that 5G networks provide widespread networking, high data rates, coverage, reliability, and low latency, and meeting such various requirements increases ICT energy consumption. According to projections, by 2025, information and communication technologies could cover about 30% of global power consumption.

Johnson (2018) tried to solve the 5G energy consumption problem by deploying small cells. According to the study, networks have become denser, increasing energy consumption.

Bjornson et al. (2013) state that to improve cellular energy efficiency without reducing the quality of service (QoS) in users, the network topology should focus on providing higher spatial reuse. According to the study, it is to decrease the total power consumption while meeting quality-of-service (QoS) constraints of users and power constraints of base stations BS and small-cell access points (SCAs).

Rajoria et al. (2018) used massive multiple-input multiple-output (MIMO), which increases power consumption due to more hardware components required. Bjornson et al. (2015) researched the optimum number of antennas, active users, and transmit power to design a multi-user MIMO system from scratch to cover a given area with maximum energy efficiency uniformly.

Haidin et al. (2021) stated that artificial intelligence and machine learning would unlock the power of software and algorithms that would permit the efficient distribution of assets and resources. In the study, a machine learning method was used to determine the critical features of a 5G production dataset to increase the energy efficiency of a 5G network.

Suomalainen et al. (2020) The challenges posed by machine learning in 5G networks and possible solutions to these challenges are discussed. The study highlights future research into the secure deployment of machine learning techniques in 5G and future wireless networks.

Tayyaba et al. (2020) proposed a resource allocation policy framework for software-defined networking SDN-based vehicle networks in the context of 5G connectivity. While concluding the paper, it is clear that the LSTM has outperformed the rest of the classification techniques with promising results. The proposed policy framework can optimize resource allocations according to changing demands and network dynamics in-vehicle networks.

Sim et al. (2018) addressed the problem of beam selection in mmWave base stations, which results in network traffic and congestion. According to the study, mmWave base stations of fast machine learning FML learn from the current context and achieve near-optimal performance within an average of 33 minutes after deployment.

Li et al. (2018) present an intelligent intrusion detection system IDS based on software-defined 5G architecture using machine learning algorithms. The combination of selected algorithms has also proven effective compared to existing solutions.

Kafle et al. (2018) investigated the necessity of 5G network slicing and automation of network functions for the design, construction, deployment, operation, control, and management of network slices. Machine learning techniques used for the applications of network functions and the status of artificial intelligence and machine learning-related activities in standards development organizations and industrial forums presented.

According to the study of Chen et al. (2018), machine learning algorithm-based physical layer channel authentication is proposed for 5G wireless communication security.

Abidi et al. (2021) started to design an efficient network slicing using a hybrid learning algorithm. The conclusion of the paper revealed that the proposed model could affect the provision of correct 5G network slicing.

Aldweesh et al. (2020) surveyed the applications of deep learning algorithms in anomaly detection. It focuses on cybersecurity defense systems for 5G wireless mobile networks.

Fang et al. (2019) explored the challenges of traditional authentication techniques and the advantages of smart authentication. Intelligent authentication design used to improve security performance in 5G and beyond wireless networks. Machine learning techniques provide a new perspective on authentication under unknown network conditions and bring intelligence to security management to achieve cost-effective, more reliable, model-independent, continuous, and state-aware authentication.

Huang et al. (2019) presented a survey on the physical layer based on the deep learning algorithm, mainly non-orthogonal multiple access (NOMA), massive MIMO, and mmWave. Current research focuses primarily on physical layers and cybersecurity defense. However, many issues were in previous surveys. Additionally, previous research focuses on a particular aspect of 5G wireless mobile networks that prevent readers from seeing the broad view of deep learning solutions in the 5G wireless mobile network.

Restuccia and Melodia (2020) are motivated by the fact that 5G wireless mobile networks rely heavily on millimeter waves (mmWave) and ultra-wideband communications. Therefore, it focuses on the physical layer of wireless mobile networks. The article discusses the importance of real-time deep learning algorithms at the physical layer.

Bhuyan et al. (2013) generally researched network traffic, and host operations with the development of generic and robust anomaly detection algorithms that deal with unknown attacks, such as AI and ML, antivirus scanner systems, intrusion detection, spam filters, and fraud detection systems - stated that it would be applied to deal with most of the applications. Relying on independent, decentralized network functions and third-party servers, the 5G and beyond network will pose a more significant threat regarding Denial of Service (DoS) and cyber attacks. Thus, domain-dedicated agents of network components can better protect those components in particular and the entire system in general. Various AI and ML solutions are used to deal with decentralized networks(Dai et al., 2019). Recent solutions use different reinforcement learning (RL) and deep reinforcement learning (DRL) techniques to deal with such attacks (Luong et al., 2019). In the case of jamming attacks where hackers corrupt radio frequency (RF) signals, DRL-based solutions are used that select appropriate frequency channels and avoid the episode using the most appropriate policy learned from previous observations. Cyber-physical attacks manipulate data to gain control of the system. Such attacks usually occur in autonomous systems such as intelligent vehicles (Ferdowsi et al., 2018). DRL used autonomous systems with the ability to learn from observations that change over time to establish optimum actions so that the system would be more robust and dynamic. DRL systems are progressing well in maintaining connectivity between robots to support efficient communication.

Gupta et al. (2015) proposed a general 5G cellular network architecture, showing that device-to-device communication (D2D) minor cell access points, network cloud, and the Internet of Things could be part of the 5G cellular network architecture. Also, Zhang et al. (2019) conducted a study on the applications of deep learning algorithms in the general field of mobile and wireless networks, unlike our proposal, which mainly focuses on 5G wireless mobile networks. Dai et al. (2019) applied deep reinforcement learning (DRL) to develop a caching scheme for the 5G mobile network and beyond. The numerical results show that the DRL caching scheme effectively maximizes the caching resource utility. Dong et al. (2019) recommend deep reinforcement learning DRL to minimize normalized energy consumption for hybrid 5G mobile network technology in edge computing systems. The digital twin in the natural network environment is used for offline training of deep reinforcement learning DRL on the central server. He noted that the proposed approach minimizes normalized energy consumption with less computational complexity better than existing approaches.

Pradhan and Das (2021) propose The reinforcement learning RL for resource reservation in highly reliable low-latency communication for 5G network. RL is used to outperform the base method in terms of packet drop probability and resource usage.

Zhao et al. (2021) proposed an RL application for a dynamic scheme of network slice resources to improve service quality in a 5G mesh-enabled smart grid. The algorithm can change the network's demand at a fast response rate to handle resource allocation.

Ho et al. (2019) proposed the application of deep q-network DQN-based 5G-V2X to optimize 5G-based station allocation for platoon vehicles. Attempt used to find a solution to the base station allocation problem.

Xie et al. (2019) applied deep q-network DQN to develop an adaptive decision scheme for the first window in 5G MEC. The method can optimize flow completion while minimizing congestion. Comparison with base algorithms shows that the proposed converges rapidly with stability. Supervised learning is used to increase the responsiveness and efficiency of the first window decision.

Li and Zhang (2020) implemented deep reinforcement learning DRL used in 5G networking to optimize the balance between quality of service and enhanced broadband and low-latency communication. Quality of service is used by a balance between improved mobile broadband and highly reliable, low-latency communication.

Yu et al. (2020) proposed deep reinforcement learning (DRL) for cloud radio access networks to maximize energy efficiency, quality, and connectivity of remote radio heads. The algorithm is used to meet user requirements and handle cell outage compensation effectively.

Mismar et al. (2019) used Deep Q-Networks (DQN) to estimate voice and data carriers in the sub-6 GHz mmWave band. -improved signal-to-noise performance plus noise ratio and overall rate capability.

Saeidian et al. (2020) proposed Deep Q-Network (DQN) downlink power control in 5G. It used the power control approach proposed by Saeidian et al. Saeidian et al. (2020) noted an improved data rate and reduction in transmitted power at the edge compared to the main methods. Abiko et al. (2019) recommend deep reinforcement learning DRL to allocate radio resources in 5G, which meets the service requirement regardless of the number of slices.

Giannopoulos et al. (2021) applied Deep Q-Networks (DQN) to improve energy efficiency in multi-channel transmission for 5G cognitive in decentralized, centralized, and transfer learning. The results showed that the deep q-networks (DQN) model could improve network energy efficiency.

Gu et al. (2021) developed the DRL knowledge-based assisted algorithm to design wireless planners for 5G networks with time sensitivity in traffic. The proposal improved service quality and shortened convergence time.

Yu et al. (2020) designed the DRL timescale, which consists of a learning process of fast and slow timescales to optimize resource allocation, computational load, and caching placement. The experiment shows that the proposed method reduces the convergence time by over 30%.

Dinh et al. (2021) applied deep q-networks (DQN) for self-optimization of access point selection based on local network state information. The proposed method used to increase efficiency and improve service quality compared to conventional methods.

Discussion

The developments in machine learning and artificial intelligence applications in the 5G network are summarized. According to the literature studies on the subject, various taxonomies used for deep learning and application in the 5G network. Challenges in current approaches to problem-solving in 5G networks based on deep learning algorithms and promising aspects as a new perspective to solve identified challenges have existed in the article. The article can be used as initial reading material by new researchers, and established researchers can use the article to quickly identify the area that requires further development of the research area, which will lead to the practical application of deep learning solutions for 5G wireless in the real world.

Indeed, emerging technologies, new radio interfaces, massive MIMO, and beamforming enabled 5G to reach bitrates over 1Gbps. However, operators also need to increase the intelligence of their networks to learn more concisely about their operating environment and make their predictions. Evolution to optimize resource usage automatically adapt and configure the network to cope with various services. This study shows that possible with artificial intelligence and different machine-learning approaches. Integrating intelligent algorithms and learning approaches requires the availability of large datasets that represent the starting point. However, AI and machine learning are used at different levels of the next-generation mobile business, or at least in 5G, sources of big data would explore. They must be carefully selected to extract as much information as possible. 5G enablers directly contribute to network performance; however, a working and efficient 5G network cannot be complete without artificial intelligence. For example, 5G provides simultaneous connectivity to multiple IoT devices, generating vast amounts of data that must be processed using machine learning and artificial intelligence. With machine learning and artificial intelligence integration, wireless providers can analyze historical data to identify dynamic change and predict user distribution. It can also predict heavy traffic, resource usage, and application types and optimize network parameters for capacity expansion. It can eliminate coverage gaps by measuring interference and using inter-site distance information. It can provide a high level of automation with its distributed ML and AI architecture at the network edge. It can perform application-based traffic routing and aggregation in heterogeneous access networks. It can perform dynamic network slicing to handle various use cases with different QoS requirements.

Conclusion

Artificial intelligence is already being incorporated into networks, focusing on reducing capital expenditure, optimizing network performance, and generating new revenue streams. Operators worldwide are already reaping the benefits of integrating AI into their networks. AI will be vital to improving customer service and enhancing the customer experience, often called "Quality of Experience (QoE). AI is used to help providers enhance the customer experience in many ways, including improving network quality and providing personalized services. AI will help communications service providers (CSPs) recoup the investments in their networks to move to 5G. Reducing operational costs and returning on network investments are vital priorities that service providers want to achieve using AI. Prioritized areas for integration of artificial intelligence used to optimize costs also manage ever-increasing network complexity. Network intelligence and automation are crucial to the evolution of 5G, IoT, and industrial digitization. As 5 G-supported technologies develop, operators must increase their network capacity.

Therefore, network management can only know the local state without knowing the internal. Machine learning can deal with this kind of fuzzy logic and uncertain reasoning. It can create a deep learning layer model in classifying or facilitating state prediction. It uses the hierarchical network structure, for example, to transform the feature representation into a new feature space layer by layer, as detailed in the first section. One of the advantages of artificial intelligence is that the system does not need the parts that require extra effort to define the mathematical model.

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