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Artificial intelligence techniques over the fifth generation mobile networks

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ABSTRACT

A well fifth generation (5G) mobile networks have been a common phrase in recent years. So, 2025 the number of devices based on 5G will reach about 100 billion, about 2.5 billion users are expected to consume more than a gigabyte (GB) of data per month. 5G will play important roles in new areas, from smart cities and mobile augmented reality, and 4,000 pixels (4K) video streaming. Bandwidth higher than the fourth generation (4G), more reliability and less latency are some of the features that distinguish this generation from previous generations. These features are impressive to a mobile network, but will pose serious challenges for operators and communications companies and will lead to complexity. Managing this network, preventing errors and minimizing latency are some of the challenges that 5G of mobile networks will bring. So, the use of artificial intelligence and machine learning is a good way to solve these challenges. In this paper, we will review the artificial intelligence techniques used in communications networks. Creating a robust and efficient communications network using artificial intelligence techniques is an incentive for future research. The importance of this issue is such that sixth generation (6G) of cellular communications. So, much emphasis on the use of artificial intelligence.

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1. INTRODUCTION

The main fifth generation mobile networks have been a common phrase in recent years. We have all heard this phrase. Obviously, there will be interesting capabilities and features in this generation that will make the use of mobile technology, and enjoyable. Fifth generation (5G) will play a significant role in a variety of new areas, from smart homes and cars to smart cities, virtual reality and mobile-based augmented reality and 4K video streaming. Bandwidth much higher than the fourth generation, more reliability and less latency are some of the features that distinguish this generation of mobile networks from previous generations. But aren't all these benefits challenges? Obviously, there must be challenges. In the future, the volume of network connections will increase significantly and it will be possible to connect numerous devices to the network; this is a very important issue for the (internet of things) IoT. By 2025, the number of devices based on the fifth generation of mobile networks will reach about 100 billion devices. By then, about 2.5 billion users are expected to consume more than a gigabyte of streamed data per month. Also, by 2025, 5G mobile edge computing (MEC) is expected to be a multi-million-dollar industry [1]. Mobile edge computing is a technology that will help satisfy the demanding requirements for throughput of network, scalability, latency, and automation in 5G networks [2]. More information on mobile edge computing can be found in [3], [4].

Increased speeds and reduced delay in 5G enable novel applications such as connected large-scale IoT, vehicles, video streaming, and industry robotics. Machine learning (ML) is leveraged within mobile edge computing to predict changes in demand based on cultural events, natural disasters, or daily commute patterns, and it prepares the network by automatically scaling up network resources as needed. Together, mobile edge computing and ML enable seamless automation of network management to reduce operational costs and enhance user experience [5]. Paper [6] provides a comprehensive review for wireless network intelligence at the edge.

One of the main concepts of fifth generation networks is the ability to connect multiple devices to each other. These connections will also lead to a complex and heterogeneous network. Managing such a complex network now requires very complex computations. Many devices around the world will be connected to the 5G network. Each connection in the target network must respond to many requests with the least delay, and these requests will become more diverse in the future with the spread of fifth generation networks. In the world of 5G, the importance of achieving fully automated infrastructure is quite clear. Managing this network requires a powerful tool. The best tools for this crucial management are machine learning (ML) and artificial intelligence (AI) and deep learning (DL). Machine learning, which is itself a kind of AI, is a good option for automation. Deep learning has also had many applications in machine vision [7] and natural language processing [8] as a subset of machine learning. AI, ML and DL are envisaged to have fundamental roles in the 5G networks [9]. The use of artificial intelligence and machine learning in communications networks can create a great revolution.

The purpose of this paper is to review and categorize the methods used by artificial intelligence in communications systems, especially 5G. This paper, with a simple and concise statement, seeks to create a general view of the applications of artificial intelligence in communication networks. Hence, this paper is more idea-oriented than previous works. Also, this study can help to understand the position of artificial intelligence to achieve more powerful communications systems. The rest of this paper is as follows. The second section provides an overview of fifth generation communications networks and its limitations. In the third section, the applications of artificial intelligence in fifth generation networks are reviewed. In the fourth section, future research is also examined.

2. FIFTH GENERATION NETWORKS

Mobile technology has undergone several generational changes, so that mobile communications from cumbersome and large, heavy and not very portable devices that only support a single service (voice) in the first generation, into an environment together. They have become increasingly sophisticated, built on integrated multi-tech networks that support millions of applications called fifth-generation networks. Figure 1 shows the generational changes of communications networks.

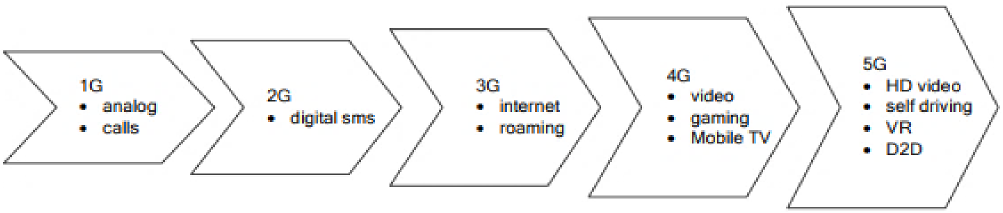

Figure 1. Evolution from 1G to 5G [1]

The 5G of mobile cellular communications is currently the newest generation of cellular mobile communication systems. The goal of 5G mobile networks, which have become available to the public in recent years, is to support audio, video, and other high-demand communications services for billions of connected devices, such as smartphones, sensors, vehicles, and other internet devices. Objects IoT stands for internet of thing. This refers to the phrase that objects and equipment of the living environment are connected to the Internet and can be controlled and managed by applications on smartphones and tablets. The 5G network is expected to revolutionize mobile technology. Because it allows users to access the Internet more quickly, while opening a new window into new industrial applications and helping to launch "smart cities". The fifth generation of mobile networks (5G) will provide high bandwidth, low latency and the ability to connect more devices. The future of 5G is related to a completely heterogeneous network (Hetnet) at various levels, which include multiple radio access technology (RAT), multiple bands, multiple cell layers, different types of devices, services, and so on. Thus, the overall planning and optimization of the radio access network (RAN) and the processes that underlie the success of the 5G concept are extremely complex.

2.1. 5G architecture

As shown in Figure 2, 5G is a convergent system that supports various applications; these applications range from mobile voice and internet gigabits per second to D2D and V2X communications (Vehicle-to-X, X stands for Infrastructure (V2I) or Vehicle (V2V)), and public safety and MTC. 3D-MIMO is used in base stations to enhance data rates and capacity at macro levels. By using relay stations, implementing very dense small cells or WiFi offloading will greatly improve the efficiency of the system in terms of coverage, capacity and energy. Directed mmWave links will be used for BS small cell and/or relay. Macros will help D2D communications by providing a level of control. Smart grid will be another application that will be realized in 5G and will allow the power grid to operate more efficiently and reliably.

Cloud computing can potentially run-on RAN and beyond, and mobile users can extract the resources they need from a shared virtual repository managed by the network. In this way, the application or applications can be brought closer to the end user to reduce communications latency and better control of real-time and delay-sensitive functions [10]. 5G is expected to integrate various RAT technologies long term evolution (LTE), high speed packet access (HSPA), global system for mobile communications (GSM) and WiFi) and new RWs in the mmWave band. MmWave technology will result in revolutionizing the mobile industry, not only due to the wide bandwidth that is available in the band (which allows the creation of Gbps wireless tubes), but also due to the reduced antenna size, the possibility of creating series antennas with hundreds or thousands of the antennas in the BS Or even gives us the user device. Smart antennas with the beamforming and phased array abilities are used to direct the beam of the antenna to the wanted location with a high accuracy. The narrow beam allows us to make the most of 3D degrees-of-freedom (DOF) without having to worry about interference with the other users. The small size of the antenna enables massive/3-D multiple-input multiple-output (MIMO) in the base stations and ultimately in the user's device. MmWave technology as well, enables ultra-broadband backhaul links to transfer traffic to the small base stations or relay stations, which increases system flexibility. Implementing very dense small cells is another 5G solution to the challenge of 1000 times the capacity. Smallcell has the potential to dramatically increase system capacity and minimize the physical distance from the base stations to the user, thereby increasing energy efficiency at 5G. The former 3GHz bands are also used for macrocells and their broad coverage, whereas higher frequency bands (such as cmWave and mmWave bands) are used for the small cells provided by the BS macro control level [10], [11].

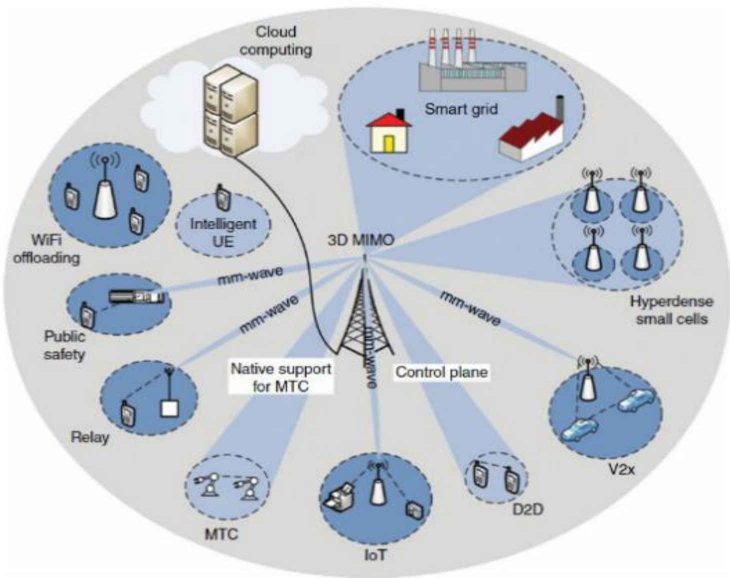

Figure 2. 5G architecture [10]

In addition to new RATs and small, dense cells, existing RATs will evolve into 5G for higher spectral gain and energy gain. The LTE-A data level latency is about 20 ms, and that is expected to be decreased to 1 ms in the future. In addition, the spectral gain of current system of the HSPA is 1bs/Hz/cell, which can be expected to be increased tenfold by the year of 2020. The energy efficiency of a cellular system is expected to be improved one thousand times by the year of 2015 compared to 2010. Medium-access control (MAC) and physical layer (PHY) layer techniques for transmitting small but delayed packets for machine-type communications (MTC) applications will be reviewed. Virtualization will also have a fundamental impact on the 5G for effective resource management; 5G is a multitenant network that not every mobile operator needs to have all the network equipment (like the base station) may be shared between a variety of the operators and even users. The current concept of cloud network mostly includes data centers. Mobile network virtualization brings such concept to backhaul and RAN for the purpose of allowing the backhaul and the BS links to be shared by different operators. Finally, we point out that the end users of 5G smartphones are multi-mode. These end users are smart enough for being capable of choosing the correct interface for the purpose of connecting to a network according to the quality of the channel, residual battery charge, energy efficiency of a variety of the RANs, and required quality of service. These smart end-users support the 5G D3 interface at 10 Gbps [10].

2.2. Fifth generation limitations

Fifth generation communications networks have limitations. Resource, power, energy and network coverage constraints are the most important of these constraints. Of course, there are other problems. Interference has always been a problem in communications networks. In a dense and large-scale IoT network, inter-cell interference problems become very important, and therefore, advanced energy allocation and interference management techniques are required. In addition, one of the major concerns of cellular communications system designers today is to reduce power consumption in order to use more battery power or reduce battery volume and weight. Along with common methods of reducing consumption in various sectors such as hardware, software and power management system is one of the effective methods of optimal use of limited energy is available. Communicating with energy saving is very important because most sensors and actuators in the internet of things (IoT) are battery operated and have limited battery capacity and charging capabilities. Designing resource allocation with appropriate efficiency and designing communication protocols is essential to provide satisfactory quality-of-service (QoS) and support in dynamic network environments. Network coverage and resource allocation limitations are very important in 5G networks. There are different tools and designs for this theme. One example is D2D connectivity.

Information was provided on fifth generation networks and their structure and objectives. As the title of this review paper suggests; in this paper, we seek to examine the role of a powerful tool in fifth generation networks to meet the challenge of the complexity of these networks. This powerful tool is the same as artificial intelligence and machine learning. Here it is better to fully define the relationship between artificial intelligence and ML. generally, the correlation between AI and ML can be expressed in such a way that ML is a branch of AI. Artificial intelligence is a term used to describe a wide range of subjects, rather than a specific technology; includes all technologies that have an aspect of intelligence. Machine learning is also a modeling method that uses data to create models. So, machine learning is a method that extracts a model from data. This data can be text, audio, video or communications channel information. The ultimate goal of the machine learning process is to achieve modeling, forecasting, and classification that can be a good solution to complex problems.

3. APPLICATIONS OF AI IN FIFTH GENERATION NETWORKS

The use of artificial intelligence and machine learning can cover various communications applications. To enable the use of artificial intelligence mechanisms to effectively manage network resources to allow users to connect without borders; the self-organized network must be introduced. This network is called self-organizing networks (SON) for short. Understand. So, SONs with clarity intend to reduce operating costs through the replacement of the traditional manual configuration, maintenance and optimization after deployment in mobile networks with auto-configuration, self-optimization and self-repair characteristics. In short, self-organized networks offer a vision in which future radio access networks will have much easier planning, configuration, management, optimization, and troubleshooting. This horizon is in line with 3GPP and nanograined metallic glass (NGMN). SON performance can be divided to 3 general classes; i) self-configuration; ii) self-optimization; iii) self-healing.

Current self-organizing networks (used in the second to fourth generations) typically track the method shown in Figure 3, in which spatio-temporal knowledge (including drive tests, OAM reports, and some other information) is obtained. Is available in full or in part. For example, it is assumed that the location of possible cover holes or ping pong (return) delivery areas is known by the SON engine. However, since SONs do not provide dynamic structures for predicting system behavior in the live operations to meet the exact latency needs of the next generation of mobile phones, the current method of the SON shouldn’t be taken under consideration in the future networks of the 5^{th} generation [12].

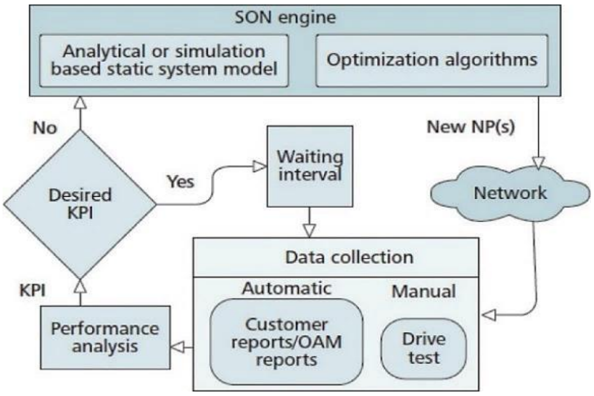

Figure 3. Self-organizing networks (SONs) in networks of the 2nd, 3rd and 4th generations [3]

Figure 4 shows a possible and general framework for SON in the fifth-generation network. As can be seen; Big data that may be summarized as vast amount of the information that is available from various sources on a mobile network, has been considered as one of the key features that distinguishes the next SON from older mobile systems. Big data sources for the SONs of the 5th generation can be divided into 3 fundamental layers at the level of the network, which are presented:

- Common-level data: such as call success rate, speech quality, call dropout ratio, IP traffic flow.
- Data at the core level of the network; such as statistics related to historical alerts, authentication and device configuration records.
- Cell surface data; such as the thermal noise power, received interference power, and channel base bandwidth.

In addition to collecting the data, the introduction of the ML tools and data analysis (such as data mining tools) makes it possible to automatically convert large (raw) data into accurate (meaningful) data. After obtaining appropriate and reliable data, the behavioral models of the system and the user may be obtained, then delivered to the engine of the SON for the purpose of achieving the proper performance of the SON.

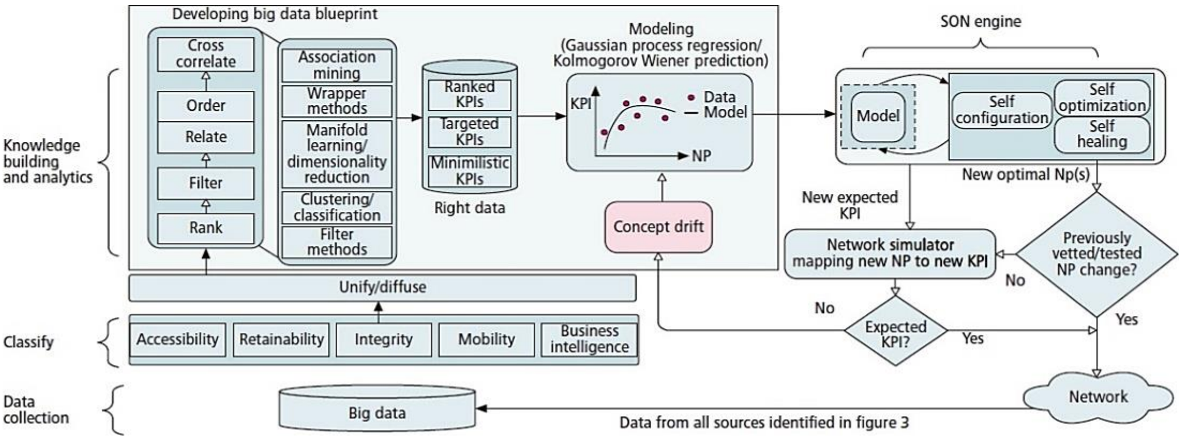

Figure 4. Expected framework for 5G self-organizing networks [12]

In short, SON enables the use of AI-based methods (eg. ML, genetic algorithms, bio-inspired algorithms, and fuzzy NNs) to effectively address the problems of complex scale systems. Great to manage. Heterogeneous networks are networks that have heterogeneous designs. HetNets heterogeneous networks have a problem because the number of network resources is constantly increasing. Artificial intelligence methods have been designed for the purpose of overcoming the large-scale system disadvantages, so they can be added to future and current HetNets for the purpose of reducing the human conflict. Such a plan is a very important goal of the SON. At that point, AI-based methods are capable of significantly reducing the operating and capital costs as well as optimizing the network coverage, capacity, and QoS in the HetNets based on the Self-X features [13]. This is a good and complete goal and a great motivation to use these techniques. The main purpose of artificial intelligence techniques is to make HetNets networks smarter.

These techniques cover a wide and varied range. Some of nature's findings are inspired, some by human reasoning methods (eg fuzzy systems) and some by feedback-based learning (eg ML) and local interactions. To understand the advantages and disadvantages of each, a detailed study of every one of the techniques and its viability has to be done in some of the network applications.

Artificial neural networks are one of the most important tools in artificial intelligence, which is based on human brain neurons. In short, ANNs mimic how the human brain operates. A neural network is created by connecting a large number of nodes (neurons) that are connected to one another using values of different weights. After learning, artificial neural networks can be used for classification. In the present day, using the intelligent systems, in particular, the ANNs, became so common that those tools may be categorized as widespread and fundamental tools in the basic mathematical operations. In ANN, as shown in Figure 5, different artificial nodes (for example, the neurons) are interconnected for the purpose of forming a network of intertwined nodes that collect the information with the use of a connects the processing method to compute. Every one of the connections between nerve cells can be assigned a numerical weight that may be adjusted to match neural networks with inputs [14]. The neural models are usually utilized for the purpose of modeling the complicated relations between the input and the output. In addition, artificial neural networks require no comprehensive knowledge of the processes of the neural functional [15]. Thus, ANNs are capable of operating in unsupervised environments and inherently perform quite well in these environments, and therefore their performance in a variety of the HetNets heterogeneous network issues for the estimation or approximation of the functions which are dependent upon numerous unknown input conditions has been analyzed [16].

The studies presented in [17], [18] can be described about artificial neural networks and their correlation with the processes of the self-optimization. This research proposes an ANN network to increase vertical manual performance (Figure 5). With the future of 5G emerging, there is an immediate demand for the development of sufficient vertical access methods, with provide the mobile terminals with the ability of roaming in a seamless manner between existing wireless networks. The suggested approaches enable users to manually adapt the environment of the destination network quickly and the performance changes can be effectively prevented.

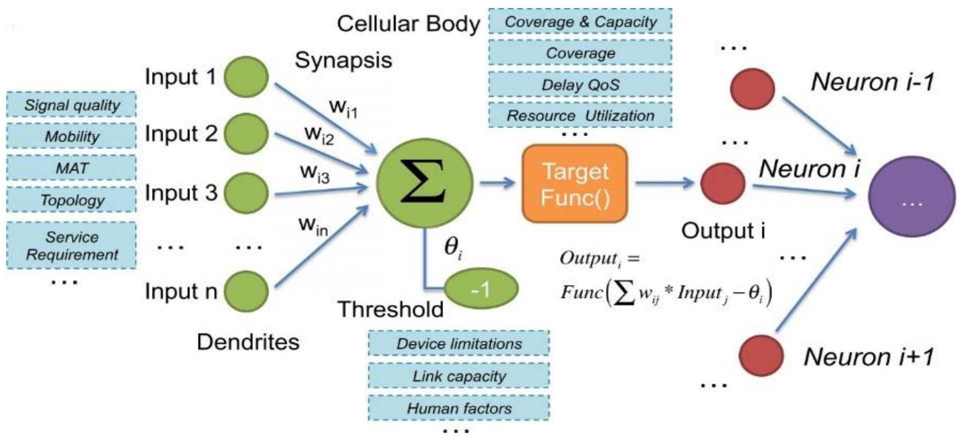

Figure 5. Use of ANN for the HetNets heterogeneous networks [4]

The fuzzy logic method seems to be suitable for controlling the incorrectness of wireless mobile networks [19]. In fact, fuzzy system techniques for controlling manual decision algorithms have recently been proposed. For example, a study in [20] proposes an access decision algorithm according to the type2 fuzzy logic that considers the types of network access and user characteristics and chooses the network that has the maximal amount of the satisfaction. A fuzzy logic transmission image in the HetNets heterogeneous networks has been illustrated in Figure 6. In addition to hand-based applications, using the concepts of fuzzy logic, as studied in [21], eICIC can be successfully used in heterogeneous HetNets networks. For some applications, defining fuzzy sets is useful in terms of more general forms of degree-degree functions. A significant form is the A: X L, where L means network. When L represents a class of the fuzzy numbers that have been defined on [0-1], fuzzy sets of type two will be obtained. This chapter was an overview of artificial intelligence techniques for heterogeneous networks; in the following, we will enter the objectives of this research a little more specialized.

Evolutionary algorithms can be used in resources to find cell programming problems and optimize node locations. For instance, the research by [22] implemented a multi-objective GA for the purpose of solving a communication node task in the HetNets. It has the aim of maximizing the coverage of the communication, in addition to its total capacity band-width, at the same time as reducing the costs of the installation. In a similar manner, the papers by [23], [24] proposed an evolutionary multi-objective approach for the 4G BS programming, in which the system capacity, signal coverage, and cost have been taken under consideration as objective functions and interference as a Constraints are considered highly important. Also, in [25] a distributed genetic algorithm has been utilized for dynamically optimizing the femtocell group coverage with adaptive adjustment of pilot power. It is possible to review other designs and ideas from the application of evolutionary algorithms in communications applications, but it is not necessary to review all of them here. Our main goal in this section of the paper is just to understand their interesting application in this field.

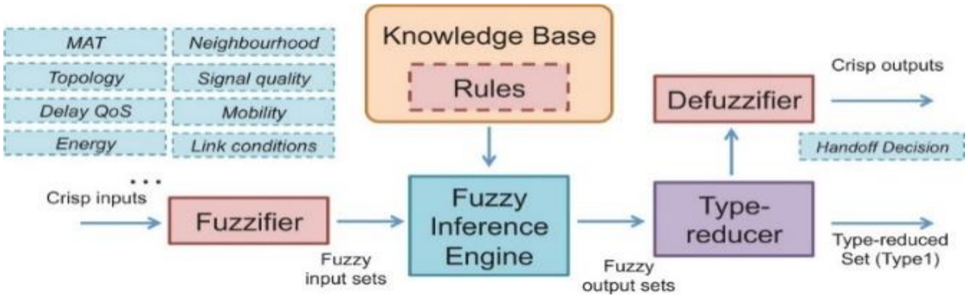

Figure 6. Fuzzy logic for the HetNets [13]

Prediction of QoS is one of the most attractive applications of machine learning in communications. As the number of connected vehicles increases and the number of sensors connected to the network increases, the network load will increase significantly and the network will face a lot of uncertainty. So, if we want to manage such a network without using machine learning, we will face a problem. Machine learning will increase efficiency and help us use new methods. Using a powerful tool called artificial intelligence, customers will experience more stable networks. This is an important achievement. In addition to the fact that customers will lose far fewer calls, service providers will be able to configure and maintain the network more easily, and the energy consumption of communications towers will be significantly reduced, which can help expand the network further. Machine learning and artificial intelligence will also help identify network problems and enable problem prediction using data analysis, thus better managing network operators and employees. In short, in the future, artificial intelligence will be present in the network and service delivery infrastructure and in the path of data transfer to devices and in the mobile devices of users. In [26], a deep neural network (DNN) is used to ensure that the QoS is in good condition during video streaming. In [27], deep networks are used to maintain and manage the QoS .

With the appearance of the new technologies, plans, and infrastructure, spending considerable radio resources on the estimation of the conditions of the channel in the mobile networks represents quite a challenge [9]. The automation of the process that is utilized for the prediction of the conditions of the channel may result in the efficient utilization of the resources. So far, [9], [28] proposed a machine learning-based approach, in other words, an ANN to predict the value of the signal to interference plus noise ratio (SINR) for the purpose of mitigating the utilization of the radio resources in the mobile networks. The scheduling of the radio resource is, in general, accomplished based on the estimated conditions of the channel, in other words, the SINR using the sounding reference signals (SRS). The suggested nonlinear auto regressive external/exogenous (NARX)-based ANN has the aim of minimizing the rate of sending SRS and achieves a $R = 0.87$ accuracy. Which may result in vacating about 4% of the spectrum, enhancing the efficiency of the bandwidth and reducing the uplink power consumption. Table 1 lists some of the papers related to this field.

The issue of security in communications networks can also be solved with artificial intelligence. In general, the purpose of an industrial intelligence algorithm in the field of security is to detect and counter the attack. Some papers, such as [29]-[31] have researched on this subject. Optimization of energy consumption in communications networks using artificial intelligence algorithms is a topic that has been followed in papers [32]-[34]. Research in this area can also be interesting. In short, by using intelligent algorithms, manual scheduling, implementation, optimization, and network maintenance activities can be substituted or supported by independent and automated processes. As a result, operating costs are decreased and human error is reduced, which is a very attractive goal and performance.

Table 1. Some of the papers related to this field

Row	Subject and Purpose	Ref
1	Cognitive autonomous networks of the5th generation	[14]
2	Handover prediction	[35]
3	Link status prediction	[35]
4	Intrusion detection system	[35]
5	Modulation classification	[36]
6	Network optimization utilizing a variety of the approaches	[36]
7	Enhancement of the QoE for the 5th generation	[37]
8	AI as Micro Service (AIMS) for data-driven intelligent traffic over networks of the5th generation	[38]
9	Monitoring and analysis of the wireless network	[39]
10	Fault Diagnosis for autonomous vehicles utilizing the SVMs	[40]
11	traffic classification, routing decisions, network security	[41]
12	predict mobility based on traffic flows between base stations	[42]
13	Object classification in 5G-enabled industry robotics.	[43]
14	traffic prediction using LTSM models	[44]
15	solving mobility problem using LTSM models	[45]
16	Minimizes delay for offloading, caching and radio resources for IoT	[46]
17	Minimizes delay and energy consumption for wireless system	[47]
18	Traffic prediction for future using demand patterns	[48]
19	Optimizes scheduling for offloaded tasks	[49], [50]

A summary of the methods and materials expressed in the form of taxonomy in Figure 7 can be expressed. All details are categorized into three levels. The first level shows the tasks of intelligent systems in communications networks. The second level shows the tools and models used. Finally, at the third level, the objectives studied in the communications networks are listed.

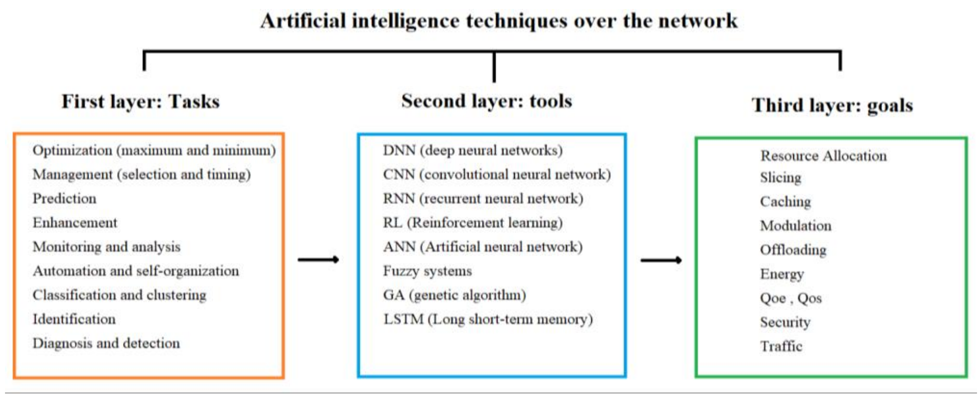

Figure 7. Taxonomy of task and Ai tools that used for network operations

4. FUTURE RESEARCH

Research on the use of artificial intelligence tools in complete communications networks is active and attractive. In recent years, the international communications union (ITU) has appointed a group called the focus group to study the technical aspects of using machine learning methods in future communications networks to work on issues such as interfaces, network architectures, protocols, algorithms and data formats. Machine learning is expected to take on some of the burden of designing, operating and optimizing 5G networks. Communications networks generate huge amounts of data that operators use to analyze users' location, cell phone movements, and call patterns, and focus group hopes that better machine-learning information can be extracted from this data. One of the challenges is that operators want to extract the information they want directly from the network (without intermediaries and doing extra work). The optimal way to do this is to process the machine learning execution resources as close to the edge as possible and use the results of their analysis to automatically control and manage the network. With the growth of technologies like the software-defined networking and network function virtualization, the ITU also anticipates that machine learning will increasingly help automate the network control process and service delivery. The team is exploring how to train, adapt, compress, and exchange different machine learning algorithms and ensure that these algorithms interact properly with each other. In these interactions, the element of network security must be considered and the privacy of individuals must be protected.

In the future, IoT and video will be the basis of communications companies' business. Many exciting future ideas are based on IoT concepts. In the not-too-distant future, we will see that more high-quality videos will be broadcast on the network platform. In order to be able to provide the best service to the customer on the network, we must use the concept of automation or digital operation. With digital operation, you can predict errors that may occur in the network and maintain network quality [51]. Digital operation will make a significant improvement in network performance and stability, as 70% of network errors (backend operations management) are caused by human errors. In addition, the ability to process customer requests and enable users to participate in finding network defects is another advantage of digital operation. AI will facilitate the network optimization process: so that backend traffic is routed according to the needs of the devices and the type of configuration, and we will reach a point that is interpreted as cloud-network synergy. In fifth-generation networks, we need new chipsets for our processors, new software architectures, new communication protocols, and artificial intelligence to optimize what the processor is doing in order to reduce network latency and increase user satisfaction. All of these needs are attractive fields for research.

An open field for research is the introduction of artificial intelligence-based algorithms that can predict network data traffic, automatically allocate network resources to meet users' needs more efficiently, and create high-quality, reliable networks. This optimization of wireless networks will make it possible to provide high-bandwidth, low-latency services in the future, which is critical to applications such as cloud virtual reality games.

The use of machine learning, and in particular deep learning in digital communications systems, can be an open and engaging issue for research. Various ideas can be put forward to improve the quality of a communications connection. For example, by combining a one-dimensional canonization network and a return network, linear code decoding can be improved. In fact, by using the potential of combining these two types of neural networks, it is possible to discover the error pattern applied to the code words that are applied to them while passing through the channel with Gaussian noise, and the original code sent by the sender with the least error on the receiver side retrieved. Also, in the field of diagnosis and classification of modulations, better results can be obtained by combining different networks. Another point is to adjust the parameters of deep learning. Since determining the parameters of deep learning models is tedious and costly work during model construction, coding methods using deep learning based on meta-exploration algorithms to determine the parameters are suggested for future research. These researches can be done in the field of model optimization or optimization of parameter values. Due to the vastness and infinity of the problem space, extra-exploratory methods are known as the best tools for this work. Other research in the field of resource management and traffic forecasting at the network level are also interesting areas. As another idea, we can investigate what data the proposed algorithms will have better results in input (audio, video). In general, we want to use deep learning as a black box to explore and understand communications channels, especially the physical layer (PHY). Therefore, the use of deep learning concepts in the field of digital communications is also expanding. Figure 8 show the use of deep learning concepts in the field of digital communications.

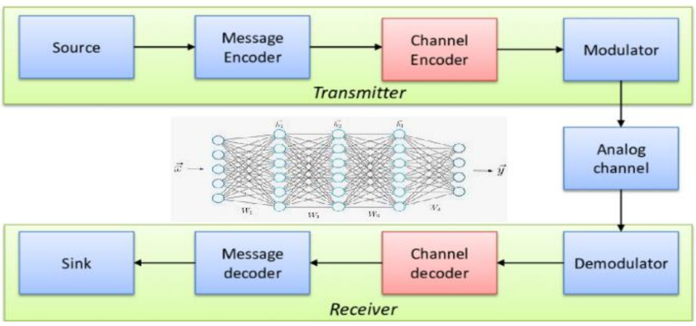

Figure 8. Use of deep learning concepts in the field of digital communications

The internet of things (IoT) is an attractive concept and is a vital field, in the telecommunications world [52]. This concept, in essence, refers to a completely homogeneous network formed through smart devices connected to the internet. In the IoT, we are faced with huge volumes and diversity of data, and machine learning (ML) and deep learning (DL) mechanisms play a pivotal role in creating intelligence in IoT networks.

The above are examples of what is happening in the field of communications and infrastructure preparation to welcome 5G. Technologies such as 5G and the Internet of Things will add to the complexity of future networks, and this complexity will negatively affect the customer experience. Artificial intelligence will enable networks to optimize themselves, improve their performance, and provide customers with the best user experience. It should also be noted that in the coming years; the sixth generation of cellular communications will be used. In the sixth generation (6G) of cellular communications [53]. There will be a lot of emphasis on artificial intelligence.

5. CONCLUSION

The 5th generation of mobile networks is the latest generation of communications systems. The future of 5G is related to a completely heterogeneous network at a variety of the levels, which include multiple RAT, multiple bands, multiple cell layers, different types of devices, services, and so on. Thus, the overall planning and optimization of the RAN and the processes that underlie the success of the 5G concept are extremely complex. To meet this challenge, the use of artificial intelligence and machine learning will be very appropriate. Using a powerful tool called artificial intelligence, customers will experience more stable networks. This is an important achievement. In addition to the fact that customers will lose far fewer calls, service providers will be able to configure and maintain the network more easily, and the energy consumption of communications towers will be significantly reduced, which can help expand the network further. Machine learning and artificial intelligence will also help identify network problems and enable problem prediction using data analysis, thus better managing network operators and employees. In short, in the future, artificial intelligence will be present in the network and service delivery infrastructure and in the path of data transfer to devices and in the mobile devices of users.

REFERENCES

[1] Wood, L. "5G Optimization: Mobile Edge Computing, APIs, and Network Slicing 2019-2024," *Technical Report for Research and Markets*: Dublin, Ireland, 22 October 2019.

[2] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile Edge Computing: A Key Technology towards 5G," *ETSI white paper*, vol. 11, no. 11, pp. 1-16, 2015.

[3] A. Yousefpour *et al*., "All one needs to know about fog computing and related edge computing paradigms: A complete survey," *Journal of Systems Architecture*, vol. 98, pp. 289330, 2019, doi: 10.1016/j.sysarc.2019.02.009.

[4] Q. Pham *et al*., A Survey of Multi-Access Edge Computing in 5G and Beyond: Fundamentals, Technology Integration, and State-of-the-Art," *IEEE Access*, vol. 8, pp. 116974-117017, 2020, doi: 10.1109/ACCESS.2020.3001277.

[5] M. McClellan, C. Cervelló-Pastor, and S. Sallent, "Deep Learning at the Mobile Edge: Opportunities for 5G Networks," *Applied Sciences*, vol. 10, no. 14, 2020, doi: 10.3390/app10144735.

[6] J. Park, S. Samarakoon, M. Bennis, and M. Debbah, "Wireless Network Intelligence at the Edge," *Proceedings of the IEEE*, vol. 107, no. 11, 2019, pp. 2204-2239, doi: 10.1109/JPROC.2019.2941458.

[7] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[8] R. Collobert and J. Weston, "A unified architecture for natural language processing: deep neural networks with multitask learning," *Proceedings of the 25th international conference on Machine learning*, 2008, pp. 160-167, doi: 10.1145/1390156.1390177.

[9] R. Ullah *et al*., "A Machine Learning Approach for 5G SINR Prediction," *Electronics*, vol. 9, no. 10, 2020, doi: 10.3390/electronics9101660.

[10] J. Rodriguez, *Fundamentals of 5G Mobile Networks*, New York, USA: John Wiley & Sons, 2015.

[11] M. A. T. Alrubei, I. A. Alshimaysawe, A. N. Hassan, and A. H. K. Khwayyir, "Capacity analysis & performance comparison of SISO, SIMO, MISO &MIMO system," *Journal of Physics: Conference Series*, 2020, doi: 10.1088/1742 6596/1530/1/012077.

[12] A. Imran, A. Zoha, and A. Abu-Dayya, "Challenges in 5G: how to empower SON with big data for enabling 5G," *IEEE Network*, vol. 28, no. 6, pp. 27-33, Nov.-Dec. 2014, doi: 10.1109/MNET.2014.6963801.

[13] X. Wang, X. Li, and V. C. M. Leung, "Artificial Intelligence-Based Techniques for Emerging Heterogeneous Network: State of the Arts, Opportunities, and Challenges," *IEEE Access*, vol. 3, pp. 1379-1391, 2015, doi: 10.1109/ACCESS.2015.2467174.

[14] S. S. Mwanje and C. Mannweiler, "Towards Cognitive Autonomous Networks in 5G," *2018 ITU Kaleidoscope: Machine Learning for a 5G Future (ITU K)*, 2018, pp. 1-8, doi: 10.23919/ITU-WT.2018.8597732.

[15] S. Haykin, *Neural Networks: A Comprehensive Foundation*, New Jersey, USA: Prentice Hall PTR, 1998.

[16] Z. Zhang, K. Long, J. Wang, and F. Dressler, "On Swarm Intelligence Inspired Self-Organized Networking: Its Bionic Mechanisms, Designing Principles and Optimization Approaches," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 1, pp. 513-537, First Quarter 2014, doi: 10.1109/SURV.2013.062613.00014.

[17] R. Chai, J. Cheng, X. Pu, and Q. Chen, "Neural Network Based Vertical Handoff Performance Enhancement in Heterogeneous Wireless Networks," *2011 7th International Conference on Wireless Communications, Networking and Mobile Computing*, 2011, pp. 1-4, doi: 10.1109/wicom.2011.6036665.

[18] A. Çalhan and C. Çeken, "An adaptive neuro-fuzzy based vertical handoff decision algorithm for wireless heterogeneous networks," *21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, 2010, pp. 2271-2276, doi: 10.1109/PIMRC.2010.5671693.

[19] K. Vasudeva, S. Dikmese, İ. Güven, A. Mehbodniya, W. Saad, and F. Adachi, "Fuzzy-Based Game Theoretic Mobility Management for Energy Efficient Operation in HetNets," *IEEE Access*, vol. 5, pp. 7542-7552, 2017, doi: 10.1109/ACCESS.2017.2689061.

[20] B. Ma and X. Liao, "Speed-adaptive vertical handoff algorithm based on fuzzy logic in vehicular heterogeneous networks," *2012 9th International Conference on Fuzzy Systems and Knowledge Discovery*, 2012, pp. 371-375, doi: 10.1109/FSKD.2012.6234358.

[21] A. Daeinabi, K. Sandrasegaran, and P. Ghosal, "An enhanced intercell interference coordination scheme using fuzzy logic controller in LTE-advanced heterogeneous networks," *2014 International Symposium on Wireless Personal Multimedia Communications (WPMC)*, 2014, pp. 520-525, doi: 10.1109/WPMC.2014.7014873.

[22] O. Abdelkhalek, S. Krichen, A. Guitouni, and S. Mitrovic-Minic, "A genetic algorithm for a multi-objective nodes placement problem in heterogeneous network infrastructure for surveillance applications," *2011 4th Joint IFIP Wireless and Mobile Networking Conference (WMNC 2011)*, 2011, pp. 1-9, doi: 10.1109/WMNC.2011.6097214.

[23] W. Mai, H. Liu, L. Chen, J. Li, and H. Xiao, "Multi-objective Evolutionary Algorithm for 4G Base Station Planning," *2013 Ninth International Conference on Computational Intelligence and Security*, 2013, pp. 85-89, doi: 10.1109/CIS.2013.25.

[24] X. Liang, H. Liu, and Q. Wang, "4G Heterogeneous Networks Base Station Planning Using Evolutionary Multi-objective Algorithm," *2015 11th International Conference on Computational Intelligence and Security (CIS)*, 2015, pp. 248-252, doi: 10.1109/CIS.2015.68.

[25] L. T. W. Ho, I. Ashraf, and H. Claussen, "Evolving femtocell coverage optimization algorithms using genetic programming," *2009 IEEE 20th International Symposium on Personal, Indoor and Mobile Radio Communications*, 2009, pp. 2132-2136, doi: 10.1109/PIMRC.2009.5450062.

[26] A. Martin *et al*., "Network Resource Allocation System for QoE-Aware Delivery of Media Services in 5G Networks," *IEEE Transactions on Broadcasting*, vol. 64, no. 2, pp. 561-574, 2018, doi: 10.1109/TBC.2018.2828608.

[27] Y. Kim, S. Kim, and H. Lim, "Reinforcement Learning Based Resource Management for Network Slicing," *Applied Sciences*, vol. 9, 2019, doi: doi: 10.3390/app9112361.

[28] N. A. Al-Shareefi, J. A. Aldhaibaini, S. A. Abbas, and H. S. Obaid, "Towards 5G millimeter-wave wireless networks: a comparative study on electro-optical upconversion technique," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 3, pp. 1471-1478, 2020, doi: 10.11591/ijeecs.v20.i3.pp1471-1478.

[29] L. Xiao, X. Wan, C. Dai, X. Du, X. Chen, and M. Guizani, "Security in Mobile Edge Caching with Reinforcement Learning," *IEEE Wireless Communications*, vol. 25, no. 3, pp. 116-122, 2018, doi: 10.1109/MWC.2018.1700291.

[30] A. Thantharate, R. Paropkari, V. Walunj, C. Beard, and P. Kankariya, "Secure5G: A Deep Learning Framework Towards a Secure Network Slicing in 5G and Beyond," *2020 10th Annual Computing and Communication Workshop and Conference (CCWC)*, 2020, pp. 0852-0857, doi: 10.1109/CCWC47524.2020.9031158.

[31] S. Truex, L. Liu, K. Chow, M. E. Gursoy, and W. Wei, "LDP-Fed: Federated Learning with Local Differential Privacy," *Proceedings of the 3rd ACM InternationalWorkshop on Edge Systems, Analytics and Networking*, 2020; pp. 61-66, doi: 10.1145/3378679.3394533.

[32] E. Strubell, A. Ganesh, and A. McCallum, "Energy and Policy Considerations for Deep Learning in NLP," *arXiv preprint arXiv: 1906.02243*, 2019.

[33] E. Ahvar, A. C. Orgerie, and A. Lebre, "Estimating Energy Consumption of Cloud, Fog and Edge Computing Infrastructures," *IEEE Transactions on Sustainable Computing*, 2019, doi: 10.1109/TSUSC.2019.2905900.

[34] W. Chen, D. Wang, and K. Li, "Multi-User Multi-Task Computation Offloading in Green Mobile Edge Cloud Computing," *IEEE Transactions on Services Computing*, vol. 12, no. 5, pp. 726-738, 1 Sept.-Oct. 2019, doi: 10.1109/TSC.2018.2826544.

[35] G. Bhutani, "Application of Machine-Learning Based Prediction Techniques in Wireless Networks," *Int. J. of Communications, Network and System Sciences*, vol. 7, no. 5, pp. 131-140, 2014, doi: 10.4236/ijcns.2014.75015.

[36] J. Wang and C. Jiang, "Machine Learning Paradigms in Wireless Network Association," in X. Shen, X. Lin, and K. Zhang; *Encyclopedia of Wireless Networks*, Switzerland: Springer, 2018, doi: 10.1007/978-3-319-32903-1_68-1.

[37] E. Ibarrola, M. Davis, C. Voisin, C. Close, and L. Cristobo, "A Machine Learning Management Model for QoE Enhancement in Next-Generation Wireless Ecosystems," *2018 ITU Kaleidoscope: Machine Learning for a 5G Future (ITU K)*, 2018, pp. 1-8, doi: 10.23919/ITU-WT.2018.8598032.

[38] G. Myoung Lee, T. Um, and J. K. Choi, "AI as a Microservice (AIMS) Over 5G Networks," *2018 ITU Kaleidoscope: Machine Learning for a 5G Future (ITU K)*, 2018, pp. 1-7, doi: 10.23919/ITU-WT.2018.8597704.

[39] P. Casas, "Machine learning models for wireless network monitoring and analysis," *2018 IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, 2018, pp. 242-247, doi: 10.1109/WCNCW.2018.8369024.

[40] Q. Shi and H. Zhang, "Fault Diagnosis of an Autonomous Vehicle With an Improved SVM Algorithm Subject to Unbalanced Datasets," *IEEE Transactions on Industrial Electronics*, vol. 68, no. 7, pp. 6248-6256, July 2021, doi: 10.1109/TIE.2020.2994868.

[41] R. Boutaba *et al*., "A Comprehensive Survey on Machine Learning for Networking: Evolution, Applications and Research Opportunities," *J.l of Int. Serv.s and Apps.*, vol. 9, no. 16, 2018, doi: 10.1186/s13174-018-0087-2.

[42] D. Bega, M. Gramaglia, M. Fiore, A. Banchs, and X. Costa-Perez, "DeepCog: Cognitive Network Management in Sliced 5G Networks with Deep Learning," *IEEE INFOCOM 2019-IEEE Conference on Computer Communications*, 2019, pp. 280-288, doi: 10.1109/INFOCOM.2019.8737488.

[43] N. G. Shakev, S. A. Ahmed, V. L. Popov, and A. V. Topalov, "Recognition and Following of Dynamic Targets by an Omnidirectional Mobile Robot using a Deep Convolutional Neural Network," *2018 International Conference on Intelligent Systems (IS)*, 2018, pp. 589-594, doi: 10.1109/IS.2018.8710581.

[44] A. Azari, P. Papapetrou, S. Denic, and G. Peters, "User Traffic Prediction for Proactive Resource Management: Learning-Powered Approaches," *2019 IEEE Global Communications Conference (GLOBECOM)*, 2019, pp. 1-6, doi: 10.1109/GLOBECOM38437.2019.9014115.

[45] M. Ozturk, M. Gogate, O. Onireti, A. Adeel, A. Hussain, and M. A. Imran, "A novel deep learning driven low-cost mobility prediction approach for 5G cellular networks: The case of the Control/Data Separation Architecture (CDSA)," *Neurocomputing*, vol. 358, pp. 479-489, 2019, doi: 10.1016/j.neucom.2019.01.031.

[46] Y. Wei, F. R. Yu, M. Song, and Z. Han, "Joint Optimization of Caching, Computing, and Radio Resources for Fog-Enabled IoT Using Natural Actor–Critic Deep Reinforcement Learning," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 2061-2073, April 2019, doi: 10.1109/JIOT.2018.2878435.

[47] J. Li, H. Gao, T. Lv, and Y. Lu, "Deep reinforcement learning based computation offloading and resource allocation for MEC," *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, 2018, pp. 1-6, doi: 10.1109/WCNC.2018.8377343.

[48] X. Wang, Z. Zhou, Z. Yang, Y. Liu, and C. Peng, "Spatio-temporal analysis and prediction of cellular traffic in metropolis," *2017 IEEE 25th International Conference on Network Protocols (ICNP)*, 2017, pp. 1-10, doi: 10.1109/ICNP.2017.8117559.

[49] Z. Ning, P. Dong, X. Wang, J. J. P. C. Rodrigues, and F. Xia, "Deep Reinforcement Learning for Vehicular Edge Computing: An Intelligent Offloading System," *ACM Transactions on Intelligent Systems and Technology*, vol. 10, no. 6, pp. 1-24, 2019, doi: 10.1145/3317572.

[50] L. Huang, X. Feng, C. Zhang, L. Qian, and Y. Wu, "Deep reinforcement learning-based joint task offloading and bandwidth allocation for multi-user mobile edge computing," *Digital Communications and Networks*, vol. 5, no. 1, pp. 10-17, 2019, doi: 10.1016/j.dcan.2018.10.003.

[51] A. N. Hassan, M. J. Mohsin, and A. H. K. Khwayyir, "Discrimination of ECG signal based on S-interpolation and Quantum Neural Network," *Annals of Tropical Medicine and Public Health*, vol. 23, no. 10, pp. 23-1039, 2020, doi: 10.36295/ASRO.2020.231039.

[52] A. Kumar, A. O. Salau, S. Gupta, and K. Paliwal, *Recent Trends in IoT and Its Requisition with IoT Built Engineering: A Review*, Singapore: Springer Nature, 2019.

[53] M. Wang, T. Zhu, T. Zhang, J. Zhang, S. Yu, and W. Zhou, "Security and privacy in 6G networks: New areas and new challenges," *Dig. Comm. and Net.*, vol. 6, no. 3, pp. 281-291, 2020, doi: 10.1016/j.dcan.2020.07.003.

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