Self-Learning and Adaptive Networking Protocols and Algorithms for 6G Edge Nodes

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2023 Fifth International Conference on Electrical, Computer and Communication Technologies (ICECCT) | 978-1-6654-9360-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICECCT56650.2023.10179645

Abstract – Edge intelligence is a new technical framework that seeks to unify Artificial Intelligence (AI), mobile edge computing, and communications networks. It is widely recognized as one of the most important missing pieces of the present 5G network, and it projected to be one of the most aspects to next-generation 6G edge-AI. This article provides a self-learning infrastructure centered on self-supervised generative adversarial networks to illustrate how automated data synthesis and learning at the networking edge might boost performance. Our 5G-connected campus shuttle system serves as a test bed for our planned self-learning architecture. The results we obtained show that the suggested architecture may successfully identify and categorize novel services in edge computing settings.

Keywords – Artificial Intelligence (AI), Service-Based Architecture (SBA), Machine Learning (ML)

I. INTRODUCTION

As part of this revolutionary shift in the wireless networking environment, 5G mobile technology is being rolled out with the potential to enable a plethora of cutting-edge applications, such as driverless cars, Internet of Things (IoT), Virtual Reality (VR), and Augmented Reality (AR) [1]. In addition, development is beginning on the 6G wireless cellular network standard, which aims to provide not only a far enhanced data transportation system but also a highly autonomous and intelligent system with a focus on people. As can be seen in **Fig. 1**, use cases have progressed from 5G to 6G.

Unique to 6G is the idea of pervasive AI, a highly adaptable framework that incorporates human-like intelligence into all network infrastructure components. The application of AI in 5G networks is already being actively pursued. The International Telecommunication Union (ITU)-T has launched a focus group concerning machine learning for next generation networking systems such as 5G "ML-5G" to advance the creation of a uniform architecture and the design of an interface for the efficient incorporation of Machine Learning (ML) into 5G as well as next-generation networks. Functional modules that are inspired by Artificial Intelligence (AI) are being developed by 3GPP enhance and monitor the performances of Service-Based Architecture (SBA). Irrespective of the promising results, broad use of AI in wireless networks has been hampered by the following three factors shown in **Table 1** below.

Table 1: Factors influencing broad use of AI in wireless networks

Factor	Impact
Limited Resources	Existing wireless networks often lack the required data storage capacity and processing power to run AI algorithms.
A Dearth of Good-Quality Labeled Data	Most state-of-the-art AI systems need a massive quantity of labeled datasets for learning and machine learning. In addition, most of the dataset generated by wireless networks is in a raw and unorganized form. Labelling this kind of data manually is time-consuming and laborious. Data collected from wireless networks is inherently chaotic, with many factors influencing how much and how well-labeled information must be for model training and development. These include, but are not limited to, network topology, user mobility, hardware and software specifications, and geographical location.
An Unoptimized Architecture for AI	Wireless network architectures as they are now envisaged were not originally thought of with the goal of enabling applications and services influenced by artificial intelligence. Artificial intelligence (AI) solutions that are resource-intensive may place additional load on an already strained wireless network. Presently, there is no AI-native connectivity architecture that can simultaneously meet the needs of delivering AI services and those of supporting a growing number of mobile applications with ever-stricter requirements.

A novel technological framework, edge intelligence aspires to bring together AI, communications systems, and mobile peripheral computing. Using edge intelligence, a large number of dispersed mobile edge servers can be set up to function and make judgements based on AI information and service requests in close proximity to their point of

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origin, paving the manner for the rapid and prevalent integration of artificial intelligence into the next era of cellular networks. As one of the most critical features missing in 5G, edge intelligence is generally identified as an essential enabler for 6G to attain the complete potentials of network intelligentization. In **Table 2** we can see how the architecture, functional elements, major requirements, and applications of AI-enabled apps in 6G vary from those in 4G and 5G.

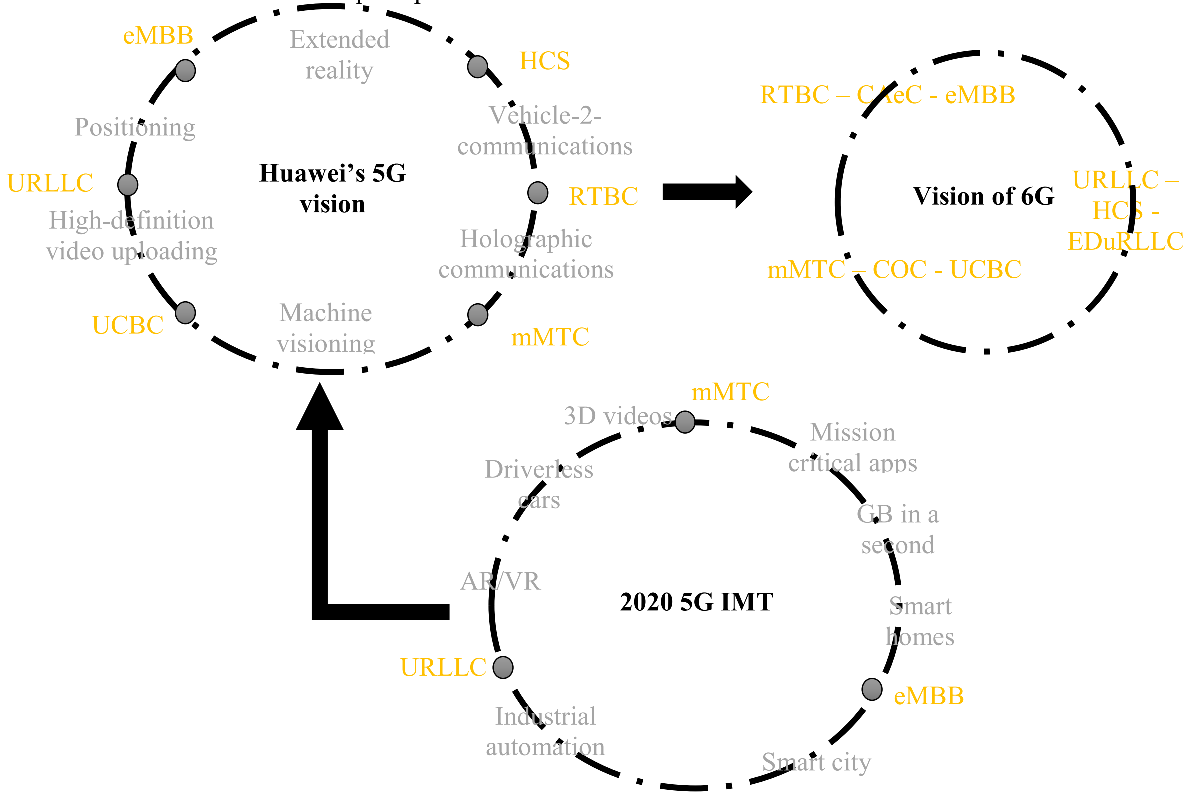

Fig. 1: the evolution of use cases from 5G to 6G.

A variety of disruptive technologies, including those for spectrum exploration, devices and circuits, networking, computation, sensing, and learning capabilities, will need to be implemented by 2030 if we want to have any say in the creation of 6G use cases. Particularly, deep learning (DL) provides a game-changing approach to the physical, medium-access, and application layers of 6G wireless network design and optimization [2].

In particular, DL provides a novel strategy for developing the 6G air interface by simultaneously improving the radio ecosystem, communications algorithms, hardware, and software. This tendency has had an impact on applications in task-oriented communication, semantic communication, and combined source-channel coding. Machine learning (ML) promises a paradigm change by dynamically learning superior efficiency and quick optimization algorithms. This allows ML to be used to the problem of resource allocation in wireless networks. By further combining domain information (such as optimisation and conceptual tools) into the DL paradigm, ultra-reliable and low-latency communication systems were optimised.

Machine learning (ML) strategies have been applied to problems in automotive application communications, connectivity, and security. As wireless data collecting, learning models and methods, and software or hardware platforms continue to improve, we anticipate that AI will become a natural tool for building revolutionary wireless technologies, therefore hastening the design, standardization, and commercialization of 6G. New learning theory, deep neural network (DNN) architectures, /specialized software, and physical hardware will all be influenced by the research and innovation of 6G wireless communication systems and communication theory.

Table 2: Objectives of artificial intelligence in 6G, 5G, 4G

	Cloud-centered AI – 4G	AI-based functionality – 5G	Edge-based AI – 6G
Architectures	Component-based infrastructures	Service-based architectures	AI-based edge-AI
Functional elements	Over the top artificial intelligence application applied in the cloud data centers delivered without the 4G network	Preset functional modules to enhance and monitor the service-based architectures' performance	Seamless incorporation of edge competing and AI communications.

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Major requirements	Mostly deployed in unsafe applications	Complex latency as well as reliability requirement in some applications such as URLLC	QoE – assure with self-learning, and self-adaptation capabilities
Application	Image and voice recognition-centered virtual assistant application	Smart factory, VR/AR, driverless cars	Self-evolving interactive communications (holographic), smart cities, humanoid robots

It is projected that by 2030, there will be about 130 billion inter-connected devices, all of which will be powered by massive-scale 6G network infrastructures. Consequently, it is critical to develop an architecture for autonomously collecting, classifying, and processing data in order to let the edge computing system to adapt and evolve on its own. Autonomous detecting, learning, logic, decision-making, adaptation, and growing without human engagement or hand-labelling is the goal of self-learning, an emerging topic under ML. It uses current breakthroughs in a broad range of AI approaches, involving self-supervised learning, auto-ML, and self-taught learning, in order to performed automated label formation, representation learning, model construction and feature extraction.

Scenario-based use cases have been suggested as a promising topic for future AI research. The fundamental contribution of this research is its elucidation of the major requirements and the trends, which will potentially propel edge-AI for 6G, mostly for ML perspectives. We recommend self-learning infrastructure and evaluate the potentials for addressing a number of most prevailing issues in 6G. To our understanding, this is the single research study to provide a wider review of self-learning and 6G application. To arrive at this ration, this paper has been organized as follows: Section II presents a critical review of 5G and 6G. Section III discusses the requirements for edge-native AI. Section IV introduces self-learning edge AI, while Section V discusses the self-learning architecture for edge intelligence. Lastly, Section VI concludes the paper with final remarks and future research directions.

II. CRITICAL REVIEW OF 5G AND 6G

A. *Fifth-Generation Network's Shortcomings*

As 5G network rollout grows to include more nations, experts weigh in on what kind of results users should expect. Let's start by looking at the pillars of 5G that are rapidly becoming outdated. Because of the widespread usage of small cells, system densification plays a significant role in 5G. Nevertheless, as more and more base stations are installed, the returns on investment, in the form of better coverage and prompt data transfer rate, show dropping returns because of the vital increment in infrastructure expenses. Carriers may aggregate their resources to increase bandwidth for their customers. However, this calls for consumer electronics to support many frequency ranges. To get beyond the limitations of end-device technology, the C-RAN (Cloud Radio Access Network) could be considered as a vital element of 5G. With the exponential growth of modern networks, however, it is becoming more apparent that computations at the fog and edge devices are also necessary.

In addition, there is not enough security in the core 5G technologies to allow for wide-scale implementation, particularly in SDNs where there is no way to verify trustworthiness between both the software installation and the controllers. Network Function Virtualization (NFV) [3] may be disrupted if an attacker accesses an application architecture, such as the virtualized computing manager, and then uses that element to generate false logs. Also, 5G's "Ultra-Reliable and Low-Latency Communication" (URLLC) is a major feature. Nevertheless, there remains a lack of actual connectivity across the network (such as the core). Furthermore, 5G technologies are based on the concept of heterogeneous networks (HetNets), but at the present moment, this kind of network integration is only possible in terrestrial networks. In order to achieve genuine 3D coverage, we must deploy mesh nodes in the heavens and beyond. It is also fundamental to remember that 5G is vulnerable to threats such as DoS (Denial of Service). Future networks may consist of billions of nodes; therefore, this will need to be considerably improved.

1) *Communication Speed and Scalability*

Between 2010 and 2030, global mobile traffic is projected to increase by 670x due to the proliferation of M2M connections. This unprecedented growth is motivating researchers around the world to find new ways to improve networking in many different areas, including spectral efficiency and energy conservation. **Fig. 2** depicts how the 5G network, with its improved mobile broadband and massive machine-type communication capabilities, can support a wide range of machines. However, it is expected that 5G's capacity will be fully utilized by 2030, meaning that it will be unable to meet future demands. Rates of data transmission will need to increase dramatically to reach well over 1 Tbps (up to 10 Tbps) in fewer than 10 years. This is because the rate of information transfer depends on user demand.

So, to effectively plan for the next generation of wireless networks after 5G, we need to look into technologies that could potentially deliver such speeds. Additionally, the mm wave range of 20-99 GHz is targeted for use in 5G technology. Nevertheless, phase frequency response, non-linear power transmitters, and low Analog to Digital Connector (ADC) resolutions are just some of the limitations of transceiver design and computer attenuation methods that make it impossible to achieve such fast velocity in this range at present. The next stage in information exchange is likely to involve experimenting with frequency range above 100 GHz, potentially up to some THz, due to the abundance of spectrum available at these higher levels. While only 4 Gbps was accomplished in the 60 GHz range, it was shown in a contrast that accelerates greater than 100 Gbps may be attained in the 300 GHz frequency band.

Because of the types of services that are still just becoming accessible or are projected to become widely employed in the next-generation, very high data rates are

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feasible. By 2020, services like AR, networked robotics, autonomous systems, human nano-chip implantation, and telemedicine are expected to be widely used. Billions upon billions of devices are projected to come inter-linked by 2030, owing to a surge in M2M communications. Optimal performance trade-offs, however, are only expected for 5G networks with a billion or more devices. As a result, the network connection will be scaled in the next major upgrade to enable the record number of connectivity options and network load.

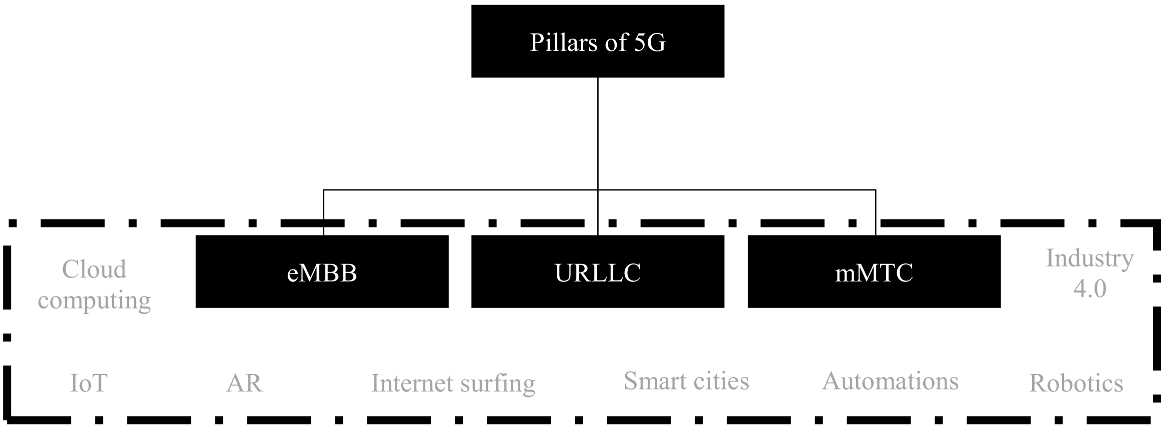

Fig. 2: 5G networking pillars with their examples

2) *Link Latency*

Multiple real-time applications have evolved in recent years, and they will continue to be an integral element of the system for several years. The services might integrate anything from aiding in construction of smart cities, e.g., autonomous vehicles and industry 4.0, to establishing novel means of interacting with the environment, e.g., VR, prosthetic limbs and exoskeletons. Various real-time services are needing minimal latency in order to operate efficiently. In addition, various technology-based problems, e.g., cyclic prefix length within the OFDM system or the usage of specialized channels for machine communications, might induce latency deterioration owing to their erratic nature of transmission.

Many applications in Industry 4.0 need concurrent sustenance for URLLC (**Fig. 2**) to attain completely automated operation without human intervention or oversight [4]. This has been considered in the most recent 5G standards release; nevertheless, this functionality is restricted to basic motion control with a maximum latency of 1 ms. The needed latency for various applications e.g., motor controls, and intra-vehicle communications for engine controls and suspensions, in milliseconds and sub-seconds (0.1 to 1 second).

For optimum functioning, many of the prior applications had many stringent criteria. For certain instances, simultaneous compatibility for super-URLLC and high data speeds is required, as seen in autonomous systems. For example, for applications like managing factories applying virtual presence, this may correspond to round-trip latencies of 250 seconds (some publications even propose 100 seconds) and a connection dependability of 109 at 10 Gbps. Over existing 5G standards, this will need 50-folds and 10-folds advancement in reliability and latency, concurrently. Moreover, 5G purposes to issue a low latency for just shorter packages. Connection dependability, modifying latency and data rates for diversified application is not completely addressed in 5G, and it hasn't been done effectively yet. As a result, it's unclear whether 5G has all of the necessary components to build smart cities that can serve a variety of machine communication needs. This allows potential for future advancements, such as ensuring improved random access (RA) mechanisms for machine communications, effectively handling increasingly complex industrial control frameworks and attaining sub-milliseconds connection latencies.

3) *Link Reliability*

It's also crucial to discuss the connections' reliability that is typically assessed by the FER (frame error rate) or BER (bit error rate). Various vital applications, e.g., vehicle-to-everything (V2X) connections [5], management of railway systems, and automation technology, require ultra-reliable connection in order to guarantee low incident rates. It is suggested that certain applications for Industry 4.0 may demand a connection dependability of up to 109 on the basis of FER; nonetheless, 5G only claims to issue up to 105. As a result, the connection's dependability must be enhanced by many orders of magnitude in order to completely execute the notion of smart cities and generally trustworthy machine activities, e.g., distant surgery. For optimal resource allocation, B5G systems will need to provide improved dependability at various levels. Link availability, which is synonymous with link dependability, is predicted to be five-nine or 99.999 percent of the time in 5G networks; however, control and automation in a given manufacturing configuration will need service presence to be 99.9999 percent. Furthermore, some studies went so far as to say that service availability for 6G networks must be seven-nine or 99.99999 percent.

B. *Sixth-Generation Network's Aspects*

Multiple new standards, needs, and possible applications are expected in the next generation of wireless technologies, known as 6G. The researchers examined 6G from a variety of perspectives, based on the hierarchy below: A broad overview of issues of communications from social, technological, and economic perspectives is included at the highest level. The medium level summarizes the key aspects of network needs, such as services, technology, and research issues. Finally, at the most fundamental level of the methodology, the researchers examine the network's

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technological operation developments, e.g., updated radio frame systems and modified RA algorithms. **Fig. 3** further elucidates the researchers' method to describing 6G.

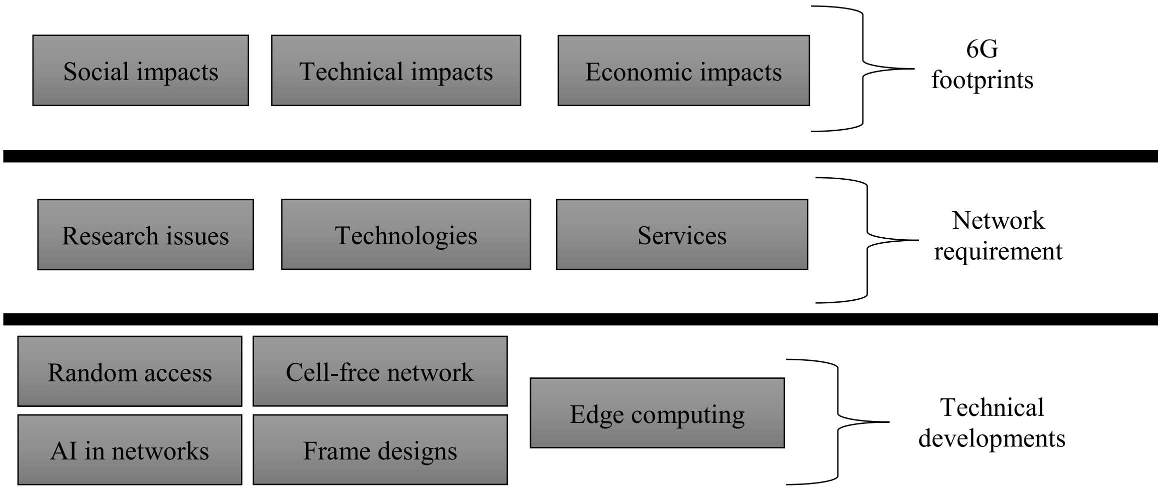

Fig. 3: A graded method for the evaluating of 6G's features.

1) 6G Network's Footprint

a) Social Impact

The field of communication networks has a number of understudied areas. Among these are the rights of users to access their own data, the pricing structures of service providers, and the general public's understanding of the value of data sharing at both the group and individual levels. For their potential to shift public opinion on delicate matters, these factors have great societal value. A controversial British political consulting company, known as Cambridge Analytica, achieved success to data via Facebook's open API, and integrate it with some publicly available data, e.g., that from only transactions, and social networking site, in order to compile more than 5,000 data points onto 290 million Americans. It was speculated that the information played a role in deciding the US presidential election. One more case in point is the standard method of spectrum allocation, whereby governments sell access to specific frequency ranges at auction. This has far-reaching repercussions, including higher costs for end users in the form of data plans, communication services, and hardware. Therefore, it is essential to propose new spectrum regulatory rules and reevaluate data access options.

In addition, the Digital 2020 July Global Statshot Report estimates that 4.57 billion people, or slightly more than half of the world's population, have access to the Internet. Connecting the world and prioritizing the installation of network infrastructure in developing countries with the lowest Internet penetration rates is a further challenge for 6G networks. This will be more apparent than ever in 2020 thanks to the effects of COVID-19, which essentially made the entire world switch to digital operations. In order to fully realize the objectives of viewing the aspect of connectively as a standard right for users, it is essential that efforts to expand the Internet account for disparities in the cost of living around the world. Providing nearly free data plans and enhancing device leasing are two means to attaining this objective. Novel internet services must consider human's variations make an effort to bring them together under one umbrella in order to overcome the global language and cultural barriers that currently exist. That is to say, it is important for network services to take into account the specifics of the geographic region serving as their primary market. An extremely visible example of this is found in Google Maps, where users in different locations see disputed territories assigned to different countries.

b) Technical Impact

With the exponential growth of technology over the last 30 years, the digital world's future is more promising than ever. It is anticipated that the most cutting-edge innovations will be available on the sixth-generation network. The succeeding sections of the study focus on the research team's elaboration of the most significant new technologies. Here, however, the researchers provide a sampling of the ways in which the digital landscape has undergone significant transformation. In 1938, the first binary-based computer was introduced, ushering in a path of development that continues to this day in the form of integrated circuits (ICs) capable of doing billions of operations in less than a second. A whole new method of computing, the Q-bit, grounded on quantum physics, is on the horizon. To put it simply, this idea proposes inspecting the state of electrons in wires in order to decode information encoded by a transmitter. Such computing has the potential to radically alter the digital landscape by allowing for hitherto impossible levels of performance and the introduction of novel network services. Integrating artificial intelligence onto the worldwide web is another case study worth considering.

By introducing various ideas, e.g., system management or self-sustainability and automated frameworks in cars, industry and various other settings, AI is altering how end devices understand communication networks. Many 6G applications and innovations are anticipated to have AI at its core, and it is anticipated that these services and technologies will be so sophisticated that humans will not be required to interfere in the operation of the network in any way. When AI reaches its full potential, it will be able to evaluate human emotions for a variety of uses, including improving the user experiences during human–bot interactions and using facial input from individual users to personalize their online content and advertising. Virtual reality (VR) is a foundational technology [6] for many existing and emerging network services, and its widespread adoption is expected to fundamentally alter how people experience and interact with their environments. During the recent COVID-19 pandemic, for instance, VR was

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employed for remote medical staff education and treatment of a patient, including VR-based neurocognitive treatment and telehealth services.

c) Economic and Environmental Impact

Especially hazardous waste from electronics, which may have a significant effect on the economy and the environment, is often disregarded. For instance, batteries contain toxic substances that would be bad for the environment if they were left out in the open. With the advent of 6G, widespread application of energy collecting through wireless waves or the laser beam in order to objectify battery-free gadgets is anticipated as a result of the technology's potential for innovation. Additionally, the yearly rise in electronic waste is at least in part due to the exponential growth in the number of Internet-connected gadgets. For instance, the quantity of electronic trash produced annually throughout the world has risen dramatically in recent years, from 14 million tons in 2005 to 42 million tons in 2014 [7]. The weight of all the electronic garbage discarded in 2017 was equivalent to seven trips to the Moon and back, or almost 11 times the weight of the Great Pyramid of Giza. Because of the prevalence of toxic substances like mercury, arsenic, and chromium in mobile devices and computers, the trend toward ever-increasing numbers is cause for concern. Consequently, it is necessary to highlight electronics reprocessing in the global telecommunications regulations of 6G, to improve the efficacy and effectiveness of the removal process, as well as to inform the public so that they may make active contributions to recycling. Chips made from environmentally friendly biological components like microorganisms might be one strategy for decreasing electronic waste and facilitating recycling with safer alternatives. One further possible upside of using green biological materials is that they could need less power to manufacture.

Meanwhile, the health risks associated with the widespread adoption of higher and higher carrier frequencies receive scant consideration. This was demonstrated in [8], which argued that millimeter waves pose thermal dangers to humans because they generate heat due to radiations. In the transition from the mm-wave to the near-THz zone, there is a corresponding increase in the degree to which we cannot know the hazards to human health and the safe levels of radiation exposure (100-900 GHz). The goal of the study cited in [9] was to identify the lowest possible exposure to terahertz radiation without causing adverse effects on human cells and tissues. The long-term effects of high-intensity terahertz radiation on human skin fibroblasts have also been studied [10]. The impacts of terahertz illumination on human anatomy and biomolecules are detailed in [11], and experiments were conducted utilizing a wide range of terahertz sources of varying intensities. Effects of terahertz radiations onto the human skin and its possible therapeutic usage in skin tissue were studied in detail in [12]. Additional research is required to establish effective standards and strict guidelines for producers of communication devices. Although technological advancements in networking have brought us closer together than ever before, they have also isolated and saddened many individuals. This has far-reaching consequences for people's mental health. In light of the sixth-generation network's promise of longer immersion experiences through novel means like nano-chip implants, it is imperative that we conduct in-depth studies to assess the gravity of the resulting socioeconomic disorders.

Since using very high frequencies results in limited coverage, the terahertz frequency range for communication should also be explored. Because of this, terahertz frequencies can only be used for communications within buildings. Moreover, tiny items, such as furniture or moving persons, may block terahertz waves, further limiting their application and utilization. For example, research presented in demonstrated that terahertz frequency bands integrated with ultra-dense BS (base stations), wideband antenna array with a relatively tiny wideband, and a restricted intensity of omni-directional nanotech are capable of reducing this impact by boosting coverage.

2) Network Requirements

Some of the network needs mentioned below, like edge computing, and network slicing, are already the subject of research on 5G and beyond 5G. Yet, investigation into these aspects of networks is in its infancy, and much remains to be done. Therefore, it's likely that it won't be until after 5G networks are in widespread use that these features can be used effectively, efficiently, and on a large scale.

a) Services

Many new kinds of services are expected to appear in the not-too-distant future to fill the needs of the twenty-first century. Here, the researchers highlight some of the most talked-about new services. It's anticipated that augmented and virtual reality (XR) will usher in a new era of human-environment interaction. Both augmented and virtual reality hold great promise for a wide range of uses, including improving safety in hazardous situations like driving by superimposing warning symbols and instructions on the road ahead. XR can also be used to give us more agency over our physical environments, like smart homes and workplaces. It is anticipated that holographic communication will enhance the interactive experience and provide novel means of interacting with one's surroundings. Holographic communication, for instance, can be used to make a dialogue between humans feel more genuine, as seen in applications like telepresence and the translation of speech into visual representations of concepts. Academic institutions, which are based majorly on virtualized open and distance learning in real-time are one example of how XR and holograms correspondence are expected to profoundly impact the future of education.

III. REQUIREMENTS FOR EDGE-NATIVE AI

In terms of the future of networking intelligentization, 6G will have a significant impact on data collecting, transport, analysis, training, and service delivery. The next iteration of edge-native AI initiatives has to meet potential requirements by 6G, which are discussed below.

A. High-Efficient AI

1) Resource-efficient AI

Optimizing the data-transfer capacity of wireless resources like networking and spectrum equipment is a primary concern for traditional wireless networks. The need to evaluate, quantify, and optimize the additional resources needed to carry out AI-based activities such as data coordination, model development, computing, caching, etc., is growing as more computationally demanding and data-driven AI features are implemented in 6G. While it is true

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that methods of artificial intelligence like deep reinforcement learning, transfer learning prototypes, and federated learning can significantly cut down on communication overhead, these methods may still require a significant number of resources when compared to the majority of data-based applications. There is also a restriction on the kind of learning challenges that may be addressed by these techniques.

2) *Data-efficient AI*

A big enough high-quality annotated dataset in every possible wireless channel and network architecture may be difficult to collect, as was previously mentioned. This is particularly true when comparing wireless systems to computer vision applications. The design approach should give top priority to self-learning technologies that need little or no hand-labeled data. Significant progress has been made in developing AI systems that efficiently use data. The self-supervised method takes use of both unsupervised and supervised AI algorithms, establishing labeling on the fly from the raw data for certain pretext goals and then using that labeling to formally train the representations. Although these methods show great promise, they are still in their infancy and can only be used for a limited set of realistic endeavors at the present time.

B. *Scalable, Distributed and Decomposable AI*

1) *Decomposable and Scalable AI*

Edge computing is a decentralized structural design made up of a large number of network edges with diverse simulation and prefetching capabilities and energy and dimensions limitations, whereas a high-performance cloud-based data hub is typically constructed on the centrally managed design and architecture with a central hub fully supported by interconnected hardware and software components. Edge services may be developed using a wide variety of operating systems and hardware architectures (such as Android, Ubuntu and Windows), and they could be distributed and maintained by a wide variety of service operators (RISC, ARM, X86). It is fundamental to provide a data and activity processing infrastructure that is both extensible and decomposable to enable the concurrent execution of operations that traverse both the internet and multiple edge servers. It's possible that peripheral devices and apps might benefit from the same network softwarization practices. Multidisciplinary hardware / software systems may be virtualized into a collection of virtual elements to carry out a variety of AI-related operations.

2) *Distributed AI*

There are many obstacles that must be overcome before edge intelligence can be widely adopted, not the least of which is the development of a simple, modular, and distributed AI strategy that will enable a substantial percentage of geographically distant network edges and cloud-based data centers to perform the same set of computing functions in concert. Federated learning as well as extension-based technologies are quite trendy right now, and this has piqued a lot of people's interest in distributed AI. However, both monolithic AI and federated learning are still in their infancy and have a long way to go before they reach maturity. Future decentralized AI-based 6G applications and services are expected to rely heavily on the federated learning-enabled infrastructure.

C. *Human-In-The-Loop AI*

1) *Personalized AI*

Because it will enable robots to properly understand and adapt human inclinations, personalized AI will contribute significantly in 6G. There are two different approaches to AI with a human in the loop. As a primary principle, we should try to use our best judgment whenever feasible. For instance, when a self-driving car encounters an unexpected situation or is unable to make a safe driving decision, it may hand over control to a human driver so that the AI program may draw on their superior reasoning abilities. The alternate approach has the agents factor in what they've learned from their interactions with people so far.

2) *Human-centered performance metrics*

It is not sufficient to optimize traditional performance metrics like bandwidth, network capability, and convergence speed when assessing and monitor the effectiveness of 6G and AI. The rising relevance of 6G and mobile networks makes it all the more important to define new metrics for evaluating the economic and social impacts of the integration of AI and 6G.

IV. SELF-LEARNING EDGE INTELLIGENCE

By enabling autonomous model production, learning, and development in reaction to variations in data characteristics and circumstances, self-learning edge intelligence may drastically reduce the amount of human effort required for data processing and model construction. For 6G self-learning edge technology to be practical, the following requirements must be satisfied.

A. *Minimized/No Human Effort*

It is widely agreed that the advancement of edge intelligence will depend on the widespread adoption of self-learning AI systems that require minimal human involvement in the form of manual information processing and labeling. Self-supervised training and formative neural network models, e.g., Generative Adversarial Networks (GANs) [13], offer an intriguing solution for training models with data that is artificially labeled but generated by the models themselves (VAEs). Next, we present a GAN-based architecture that does not require human supervision as well as provide a scenario study that shows how automatic pseudo-labeling and information synthesis can be used to discover and categorize new services.

B. *Automatic Model Construction and Search*

It is well-known that each Machine Learning (ML) system and algorithm has its own unique architecture and often includes a suite of complex techniques or empirical recommendations for building and honing the model. The field of research identified as AutoML (automatic ML) has only been around for a short period of time. The goal of the automated comparison tool AutoML is to expedite and normalize the search for appropriate machine learning frameworks and models. Both commercial enterprises and academic institutions have shown keen interest. Implementing self-learning ambient intelligence digital infrastructure requires the creation of efficient but simple AutoML solutions.

C. *Self-adaptation and Self-evolution*

The vast majority of present-day AI techniques base their decision-making only on the results of a previously

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learned model or policy, which assumes that the systems context will stay static throughout time. For example, supervised learning, one of the most well-understood but sophisticated AI techniques, necessitates training information that has been precisely labeled, and for which the operator has a complete comprehension of all possible patterns. These approaches can't keep up with changing conditions. Digital training and reinforcement learning-based techniques that attempt to optimize the long-term reward might assist solve the aforementioned problems. AlphaGo, developed by Google, employed deep learning approach to surpass the globe's top human Go players. In addition to responding to a variety of known conditions, self-learning edge AI ought to be able to apply the knowledge in the face of uncertainty. Data synthesis is more likely to succeed when used to the problem of discovering and classifying novel, unexpected scenarios from a restricted amount of real-world dataset. The following section will show how we might surpass traditional clustering methods by synthesizing data in novel ways to better identify and classify already-known services.

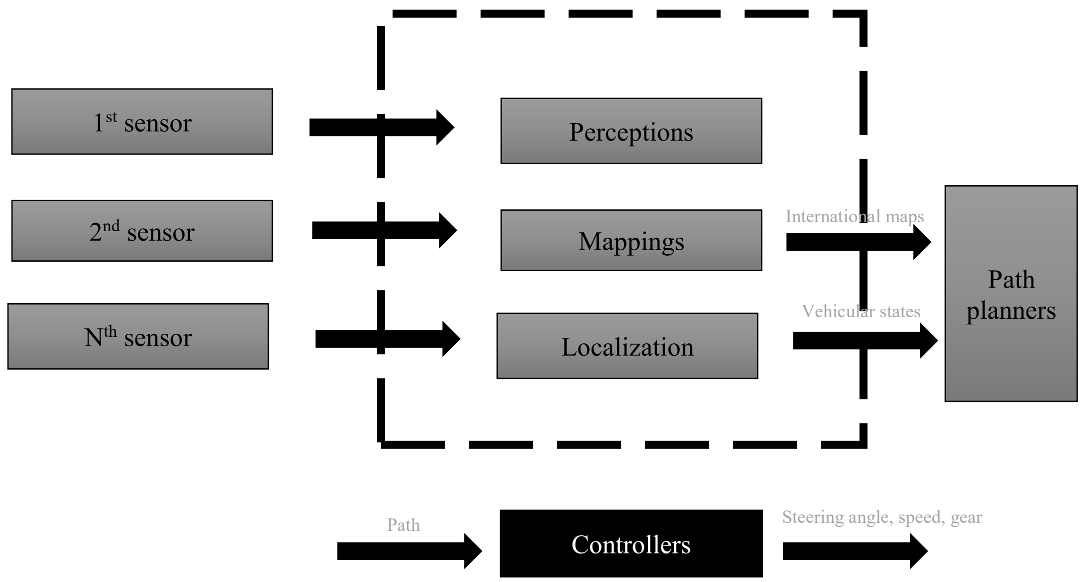

Fig. 4: An interlinked vehicular model for assessing the performance of our projected self-learning infrastructure

V. A SELF-LEARNING ARCHITECTURE FOR EDGE INTELLIGENCE

For 6G to be successful, it is essential to have an edge computing solution that is both easy to implement and capable of adapting to changing conditions on its own. In this contribution, we present a modest self-learning architecture to illustrate how a distributed edge computing system may possibly outperform current approaches to unidentified service traffic prediction and classification. In this research, we put our proposed architecture to the test in a number of real-world scenarios, using the inter-linked vehicular model as a case scenario.

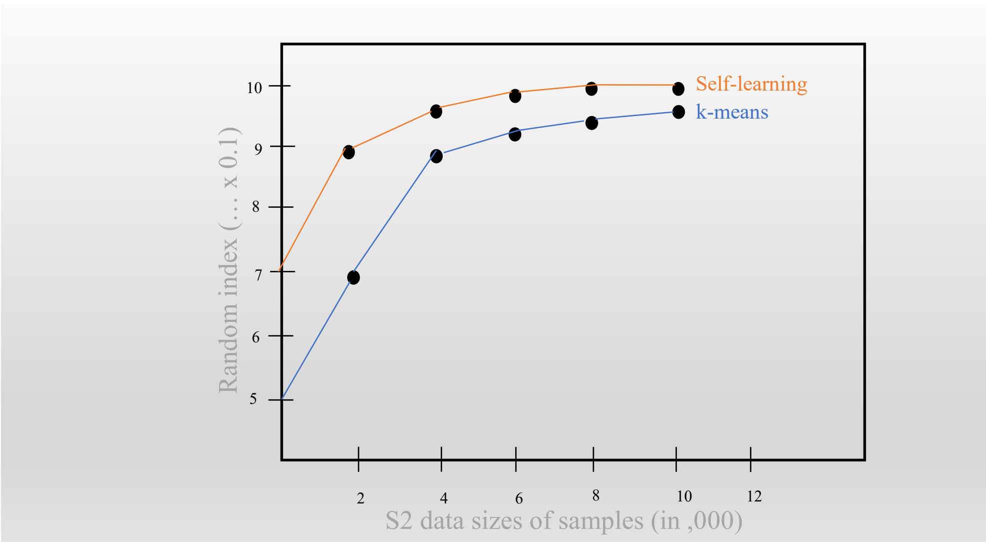

Fig. 5: Classifications performance of the projected infrastructure

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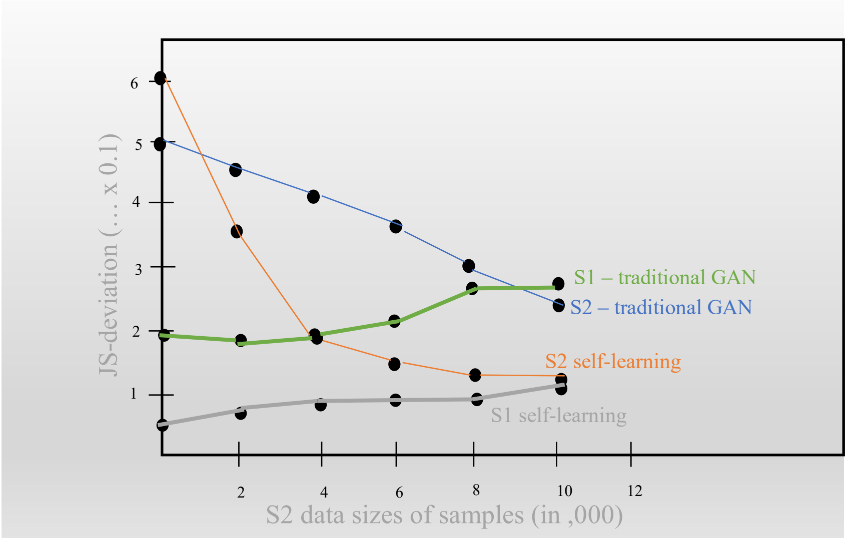

Fig. 6: JS-deviation between real and synthetic data for S1 and S2 under various data sizes of S2

A. *Self-learning Architecture*

Specifically, we offer a novel framework based on self-learned GAN have autonomous generators, which can autonomously learn features and generate ML models to detect and categorize previously undiscovered applications from raw crowdsourcing data scattered across a vast geographical region. To correctly depict the diverse nature of traffic data produced by multiple services situated in different parts of the broadcast area, our suggested architecture makes use of the GANs concept's generative learning capability, wherein several generators are taught to generate synthetic data. By incorporating a classifiers whose objective is to increase the allocation distinction (e.g., as evaluated by Kullback-Leibler (KL) Deviation) [14] between measurements of simulated data created by various generating units, we demonstrate that it is possible to learn each system to generate sample data of simulated data with similar dispersion as the prevailing traffic data based on every service. The next stage is to create pseudo-labels for the fake data output by each generator using the self-supervised learning approach. To detect and categorize data over the full service region, a deep neural network models will be trained using these false labels.

The suggested scheme differs from traditional GANs in that its discriminators should concurrently establish (i) whether or not the data is fake, and (ii) where the generator of datasets is linked with. Generators may be taught to generate sequence data that are very close to the authentic recordings, even though it has no knowledge of these mechanisms. The equilibrium point is reached when the generator and classifier optimize mutually exclusive functions. Distributing the generators and classification techniques of the proposed system across multiple edge servers allows for the model to be trained using a variety of subsets of the data, reducing the computational load on any one server. Transfer learning could be used to take advantage of the data and models generated by other users or network nodes, lowering the computational burden of learning our GANs-inspired design.

B. *Application Scenario Performance Evaluation*

We put our suggested architecture to the test by simulating a latency-sensitive interconnected vehicular architecture composed of six campus vehicles connected to two network edges and a cloud-based database servers through a 5G connection. To track the latency of data transfers on 5G networks connecting moving vehicular systems to associated edge servers and a cloud datanbased server from a key service provider, we developed a dedicated smartphone app, as shown in **Fig. 4**. To achieve this, we run a simulation of the interactions between two anonymous, parallel automobiles (S1 and S2) that have different tolerances for delay. Only Service S1 in our catalog is totally dependent on the geographical location of the nearest edge server to the end user. S2 is a hybrid edge/cloud service because its processing is split between the cloud and local nodes. We assume that vehicles only have access to aggregated data on service latency and cannot distinguish between delays caused by slow edge servers and those caused by the cloud. The suggested self-learning architecture uses a single classifier and two generators to classify latency metrics related to different services. Two services, S1 and S2, coexist and communicate data in varied degrees, and we look at what happens when they do so.

We contrast the rand index (RI) of our framework's clustering remedies to that of current systems like k-means whenever the dataset samples of service S2 change in order to assess the efficacy of our proposed architecture for service classification (see **Fig. 5**). While there are fewer data samples for service S2 in the combined dataset, the RI of our proposed architecture is still very close to 1. (the probability of a wrong clusterinng choice is nearer to 0). By calculating the Jensen-Shannon (JS) deviation between the distributions of real and synthetic data, we can evaluate the accuracy of the synthesized samples of data produced by our infrastructure (see **Fig. 6**). Employing our recommended model, we discover that the dividends of the synthetic data for both solutions are very close to the distribution functions of the real data for both services. Our suggested architecture eliminates the need for a physically labeled dataset by classifying unidentified solutions from a broad range of service metadata.

C. *Potentials to Meet 6G Requirements*

To make it possible to meet the wide array of 6G requirement, the above self-learning architecture might be modified.

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1) *Highly-efficient Edge-AI*

In the aforementioned design, the deep generated neural network's main purpose is to generate artificial information/data, which mimics the features of critical service data. This eliminates the need to collect a huge quantity of well data points for every service over the whole area of coverage. Both the amount of data uploaded by users and the amount of network traffic may be greatly decreased if synthetic data can be created remotely on the edge server. In this exploratory work, we also discover that the supercomputing intricacy of every network edge to undertake the self-supervised GAN methodology is limited when the dataset dimensions and diversity among network edge are limited. This is the case when each edge node encompasses a narrower range with a diminished service demand.

2) *Self-evolution and Self-adaptation at the Edge*

Due to differences in software solutions, application situations, user desire, etc., the statistical aspects of datasets acquired by various devices might vary greatly. The self-learning infrastructure creates simulated data that accurately replicates the dispersion of the initial source data input and could mechanically adjust to alterations in data kinds and feature interplay. New advances in combining several cutting-edge AI techniques, such as semi-supervised learning, federated learning, transfer learning, reinforcement learning, and autoML, have the potential to increase both the breadth and depth of solutions for self-learning design.

3) *Applicabilities of Human-In-The-Loop AI*

Taking advantage of human users' prior acquired wisdom and most desired services has the potential to further improve the efficacy of the aforementioned architecture. Particularly, the self-supervised learning approach can benefit from direct use of human expertise or any other kind of background information to provide supplementary pretext tasks, leading to even enhanced efficiency in the self-learning domain. Agents or framework elements can learn from their interactions with humans and adapt to their environment using this architecture.

VI. CONCLUSION AND FUTURE RESEARCH

There will be a variety of attacks made against AI-enabled 6G, all with the same aim in mind: to reduce trust in the system's capacity to learn from data and make decisions. Building resilient self-adaptive systems is essential for successfully learning, identifying, and countering these threats. Data obfuscation and poisoning attacks are rampant, and there are no existing viable countermeasures to stop them. Inputting the stolen data into a self-learning system designed to withstand several types of assaults is one approach. With a thorough understanding of how these attacks affect model learning and data processing, network providers might use replay-with-simulating and other existing technologies to safeguard the trained model. Within the framework of autonomously learning AI, this paper provided an introduction to a potential direction for future study of 6G edge intelligence. We are aware of the potential requirements and challenges associated with implementing edge-native AI in 6G. To get around the fundamental difficulties of incorporating AI in cellular interconnection, such as a lack of annotated data, a lack of suitable resources, and a dearth of an AI-optimized configuration, we tackled a self-learning framework that supports autonomous data learning and perception at the network's edge. We test our recommended self-learning architecture using a campus transport system that communicates with edge processing units via a 5G network. Our research shows that our suggested architecture may significantly boost the effectiveness of data categorization and synthesis for unidentified applications in an edge intelligence system. Other innovative and tough concerns in 6G edge intelligence, and how self-learning AI may help with them, are also covered. We anticipate that this study will serve as a jumping off point for researchers interested in the future of self-learning and its potential applications in 6G technology at the network's periphery, the edge.

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