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Review

The Impact of 6G-IoT Technologies on the Development of Agriculture 5.0: A Review

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Abstract: Throughout human history, agriculture has undergone a series of progressive transformations based on ever-evolving technologies in an effort to increase productivity and profitability. Over the years, farming methods have evolved significantly, progressing from Agriculture 1.0, which relied on primitive tools, to Agriculture 2.0, which incorporated machinery and advanced farming practices, and subsequently to Agriculture 3.0, which emphasized mechanization and employed intelligent machinery and technology to enhance productivity levels. To further automate and increase agricultural productivity while minimizing agricultural inputs and pollutants, a new approach to agricultural management based on the concepts of the fourth industrial revolution is being embraced gradually. This approach is referred to as "Agriculture 4.0" and is mainly implemented through the use of Internet of Things (IoT) technologies, enabling the remote control of sensors and actuators and the efficient collection and transfer of data. In addition, fueled by technologies such as robotics, artificial intelligence, quantum sensing, and four-dimensional communication, a new form of smart agriculture, called "Agriculture 5.0," is now emerging. Agriculture 5.0 can exploit the growing 5G network infrastructure as a basis. However, only 6G-IoT networks will be able to offer the technological advances that will allow the full expansion of Agriculture 5.0, as can be inferred from the relevant scientific literature and research. In this article, we first introduce the scope of Agriculture 5.0 as well as the key features and technologies that will be leveraged in the much-anticipated 6G-IoT communication systems. We then highlight the importance and influence of these developing technologies in the further advancement of smart agriculture and conclude with a discussion of future challenges and opportunities.

Keywords: 6G-IoT; Agriculture 5.0; artificial intelligence (AI); Internet of Things (IoT); smart agriculture; wireless communications

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1. Introduction

Recent advancements in smart devices and wireless communication technologies have facilitated the development of the Internet of Things (IoT), which exploits devices' pervasive sensing and communication/computing capabilities [1]. IoT is conceptualized more precisely as a network of physical objects comprising hardware, software, sensors, and actuators. It aims to facilitate the collection and transmission of measurement data to data centers, where they can be stored and analyzed. Recent literature demonstrates that IoT applications extend across a wide range of research fields, such as smart cities [2], environmental applications (weather forecasting, air quality forecasting, etc.) [3], healthcare [4], and smart agriculture [5].

In an agricultural context, IoT plays a pivotal role in advancing smart agriculture [6]. Indeed, one of the primary reasons the agricultural sector is capable of gathering and utilizing a substantial amount of useful data is the development and diffusion of IoT technologies. Future advancements in these technologies are envisaged to have a similar effect and to play a key role in the further development of the agricultural sector [7]. Current IoT systems rely mostly on wireless communication technologies to acquire and transmit data throughout the network. However, choosing the appropriate wireless technology is crucial, as it directly affects both the capabilities as well as the deployment and operational cost of an IoT system. Consequently, new approaches to the design and evaluation of IoT systems are developing, which emphasize that an IoT system must not only be technically sound, but also financially sustainable and have the highest market adoption prospects [8,9].

IoT wireless communications support a wide range of bandwidths and data rates, from Ultra Narrow Band (UNB) and Narrow Band (NB) communications, such as SigFox, NB-IoT and LTE-M (Long Term Evolution for Machines), to wideband cellular communication systems, such as LTE-Advanced [10,11], up to ultra-wideband 5G [12]. The new wave of wireless communication technologies for the development of future IoT systems includes research performed on 6G wireless networks [13] and their accompanying technological trends. Although Sigfox, LoRa, NB-IoT, and LTE-M are low-power narrowband communication networks that are, more or less, tailored to the needs of current smart agricultural deployments where the amount of gathered field data is relatively low, they will face challenges in meeting the extensive requirements of future IoT applications in the coming decade. Therefore, in this study, we aim to provide researchers with a comprehensive overview of existing research and to analyze possible research directions.

6G wireless networks are expected to be a significant enabler of future smart IoT applications by integrating the entire system's functionality, including sensing, data computation, and transmission, as well as fully automated control, and providing four-dimensional coverage [14]. In addition, 6G networks are expected to have improved coverage and enhanced adaptability compared to their predecessor (5G), resulting in better IoT connectivity and, consequently, optimal service delivery [15]. Consequently, it is anticipated that 6G communications will serve as a new architectural foundation for the implementation of a wide range of novel IoT applications [16].

In a nutshell, the following are the primary scientific contributions of this study: first, we introduce the Agriculture 5.0 research field, which is an improved version of current precision agriculture. By applying and embracing existing precision agriculture concepts and combining them with emerging technologies such as quantum sensing, robotics, advanced wireless network coverage, and artificial intelligence (AI), we demonstrate that new research opportunities can emerge that can significantly expand this research field. Then, we discuss the emerging 6G-IoT technologies, highlighting their significance and impact in Agriculture 5.0 applications, particularly in terms of QoS, reliability, and security.

The remainder of the current study is divided into four sections: Section 2 describes past and present forms of agriculture and introduces the emergent form of smart agriculture, Agriculture 5.0. In Section 3, the key advantages, characteristics, and challenges of 6G-IoT communication technologies are outlined, whereas in Section 4, the impact of 6G technologies on Agriculture 5.0 applications is discussed. Section 5 concludes our study with a synopsis and a discussion of future challenges.

2. Agriculture 5.0: Revolutionizing Agriculture with Cutting-Edge Technologies

Agriculture is, and always will be, transformed by new technologies so as to move to a higher level of both productivity and profitability. This section traces the evolution of agriculture from traditional farming to Agriculture 4.0, in which data-driven technologies are used to optimize farming operations. Then, we investigate the potential of Agriculture 5.0, which aims to employ even more sophisticated technologies to improve the productivity, sustainability, and profitability of the agriculture industry.

2.1. Evolution of Agriculture: From Traditional Farming to Agriculture 5.0

Following a technological evolution-based classification of agriculture eras as proposed in the related scientific literature [17,18], we can identify four distinct eras: Agriculture 1.0, Agriculture 2.0, Agriculture 3.0, and Agriculture 4.0. More specifically, Agriculture 1.0 describes agriculture from ancient times to about the 1920s, when farming consisted of a lot of manual work [19]. Agriculture 2.0, ranging from 1920 to 2010, describes the model in which machines, fertilizers, and better seeds were incorporated to help farmers produce more with less effort. This era began in earnest in the 1950s, when agronomic practices and new tools were allowed and created what is now known as agribusiness or industrial agriculture [19]. In the 20th century, Agriculture 3.0 marked a new age for more efficient and intelligent operations performed by machinery. Nowadays, the evolution of smart agriculture has led to Agriculture 4.0, integrating high-tech sensors, cloud computing, specialized software, and the IoT into farming [20]. In this new age of agriculture, data become crucial, as they are used to help farmers exploit their land, water, and fertilizers more efficiently. Agriculture 4.0 enabled the development of an environment in which all components are effortlessly and continuously interconnected [21]. This approach was established when data management and telematics were coupled with the precision agriculture concept, thus boosting procedure accuracy. Referred to as digital farming or smart farming, Agriculture 4.0 includes technologies that generate information that is then processed to facilitate operational and strategic decisions [22].

Advanced management systems are providing viable solutions in the field of smart farming. Moreover, despite the fact that some farmers have years of field expertise, technology could offer a systematic approach for discovering unanticipated problems that are difficult to recognize through sporadic visual inspection. Young farmers are consequently more positive about using current agricultural technology than older farmers since they can balance their limited field experience with new information-providing analytical methodologies [22].

Nevertheless, the average age of farmers has increased significantly in recent decades. In both the United States and Europe, it is about 58 years of age; in Sub-Saharan Africa it is 60; and in Japan, it is 63 [23]. This pattern, hopefully, is likely to be upended as several European policies, for example, are now being adopted to promote opportunities for early investments, financing, entrepreneurial guidance, and mentoring in order to encourage new generations to step forward [23]. Generational renewal in the context of rural growth means not only decreasing the average age of farmers but also equipping a future generation of highly knowledgeable and skilled farmers to fully exploit the potential of technology in order to support sustainable agricultural methods [24]. As a result, young farmers will have the opportunity to modernize and increase the competitiveness of their existing agricultural businesses. This will ensure the continuation of sustainable food production while enhancing the competitiveness of the agri-food supply chain.

Farmers can employ data-driven agriculture techniques for a variety of purposes, including strategic planning, real-time monitoring, performance evaluation, predictive forecasting, optimization, and effective event management. However, the widespread adoption of these techniques has been hampered by a number of obstacles, such as limited connectivity solutions as well as expensive and, in some cases, inaccurate data collection. Despite early obstacles, smart farming has made significant advances in recent years, with information and communications technology (ICT) demonstrating its value in the agricultural sector [25]. Overall, adopting data-driven strategies has proven to increase agricultural productivity by increasing crop yields, reducing input costs, and minimizing crop loss. According to the Global Smart Farming Market Forecast, the market is anticipated to experience substantial growth, with projections estimating its value will rise from USD 12.80 billion in 2021 to USD 33.69 billion by 2029 [26], providing a reliable assessment of the expected impact of ICT on agriculture.

Even so, major technical challenges typically elicit major solutions via disruptive technologies, and the concept of Agriculture 5.0 is likely to be seen as such in the first half of the 21st century. Agriculture 5.0, as stated previously, is based on the principles of precision agriculture and thus involves the use of autonomous decision support systems and unmanned operations [18]. Consequently, this type of smart agriculture entails the use of robotics in conjunction with various AI-based mechanisms [27], as illustrated in Figure 1, which depicts an example of a crop management life cycle.

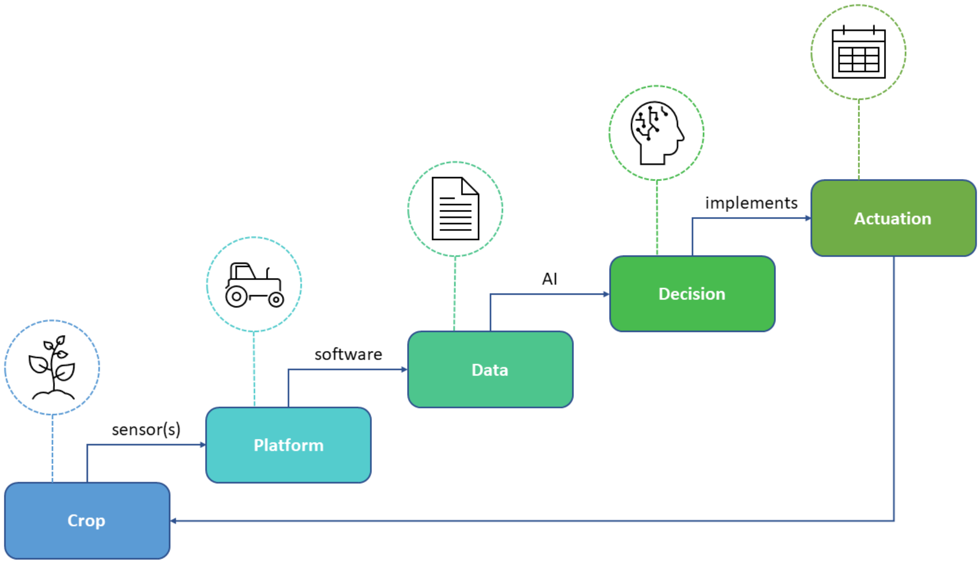

Figure 1. The concept of Agriculture 5.0 along a crop management life cycle.

Historically, the harvesting of crops from farmlands required large numbers of seasonal laborers. Nonetheless, due to the transformation of the current social regime from a rural one in which many people previously lived on farms to a city-based one, farms now face a labor shortage. According to a Forbes article [28], farm robots with AI features are the solution to this shortage, as they can augment human labor by harvesting crops at a faster pace and higher volume. However, in many cases, human labor remains more efficient than robot labor, so the smart IoT systems of Agriculture 5.0 aim to develop robotic farming systems to assist farmers with repetitive tasks [29–31].

Therefore, robotic systems for Agriculture 5.0 applications are developing exponentially [32], offering promising solutions in dealing with a long-time declining profitability and labor shortage. In this regard, Reddy et al. [33] revealed that the introduction of robotics in agriculture dramatically increased the productivity of several countries while simultaneously reducing farm operating costs. However, as with many innovations in their early stages, important limitations need to be dealt with. One of the biggest current limitations of such proposed technologies is their cost, as for most small farmers, such robotic applications still remain too expensive [34] due to scale economics that cause small individual farms to be less profitable [35].

However, as global agricultural productivity and crop yields slowed in 2015, robots were introduced as a potential solution to address these challenges and the growing demand for high yields. Therefore, agricultural robots are increasingly utilized, and the cost of the technology continuously decreases [36]. We also anticipate a steady rise in the usage of farm robots in the future, which will aid farmers in performing their duties more efficiently and effectively, to the benefit of the agricultural sector worldwide [37].

2.2. The Ultra-High Requirements of Agriculture 5.0

In addition to financial constraints, the latency, security, and reliability of the supporting communication network are critical success factors for implementing effective cloud-based AI control mechanisms in autonomous robotic systems. Furthermore, the need to reduce energy consumption while also dealing with the increased cost of agricultural inputs such as fertilizers, herbicides, and insecticides necessitates technological solutions that either do not currently exist or are in their early stages of development and are not ready for large-scale adoption [18]. Following are some examples of precision agriculture use cases that require novel technology solutions to be applied efficiently and on a wide scale.

2.2.1. High-Density and Ultra-High Precision Sensing at the Plant Level

In the current version of precision agriculture, sensors are sparsely scattered over a vast region to provide a rough perspective of the conditions occurring in that area [38]. However, it is expected that, in the future, a far more comprehensive and detailed view will be achievable by employing a much higher density of sensors [39]. One of the most exciting concepts that is slowly taking shape and is expected to be fully implemented on a large scale in the future is the possibility of collecting information at the plant level by installing sensors at each plant, as shown in Figure 2.

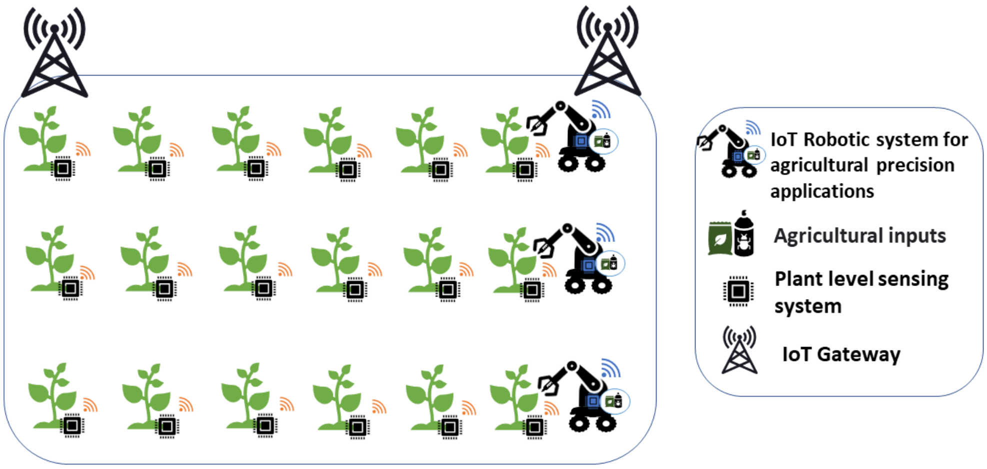

Figure 2. High-density and ultra-high-precision sensing at the plant level.

As each plant responds differently to environmental elements such as soil and weather, this approach will enable us to meet the specific needs of each plant. This ensures that the optimal amount of inputs is utilized at all times, which benefits both the farmer and the end consumer. However, even assuming a very low planting density of 2 plants per square meter, this results in a total of 2,000,000 sensors per square kilometer, which is well beyond the capabilities of the currently developing 5G networks [39–41].

The next logical step, given the availability of such a dense network of sensors, is to improve the precision of each individual sensor. Improved sensors are required not only to identify the exact location of each plant more accurately and reliably, but also to diagnose its health in greater detail, so that subsequent troubleshooting actions are equally precise and effective. This enables a precise diagnosis to be made for each plant individually, allowing for the best course of action to be determined, such as whether chemicals should be applied to the plant's roots or leaves, or even injected using microneedles [42].

Consequently, applying liquid fertilizers or pesticides in an environmentally friendly and precise manner increases their effectiveness, which can reduce the use of hazardous and polluting plant protection chemicals by as much as 95%, resulting in more sustainable products [43]. Evidently, the aforementioned processes will be more efficient the more precise the sensor measurements are. Significant development has been realized in recent years in the field of quantum sensors, which appear to be a very promising technology for multiplying the sensing capacity of IoT monitoring systems. In conclusion, the ability to collect data with high precision and spatial density would enable artificial intelligence data analysis tools to provide more precise and efficient action predictions, resulting in increased yields with reduced energy and environmental costs [44,45].

2.2.2. Large-Scale Deployment, Sustainability, and Accountability

By definition, rural locations are remote and, in most cases, lack adequate network coverage. Due to the low magnitude of the transmitted data, this is not a serious issue for the existing precision agricultural systems [46]. In Agriculture 5.0, however, we acknowledge that the issues that arise in terms of required network capacity, latency, and reliability may well be insurmountable with the currently deployed networks due to the vast density of sensors and the amount of data exchanged. Furthermore, these issues are amplified when cultivating extremely remote locations in accordance with Agriculture 5.0's objective of maximizing the use of all arable land [22,47].

Agriculture 5.0 is anticipated to impose policies and requirements on the economic, environmental, and social levels, with each level adopting the technologies, agricultural practices, and economic dimensions that will support this new vision [48]. In this direction, sustainable Agriculture 5.0 is committed to meeting people's immediate and long-term needs for food and fibers while preserving and enhancing the living conditions of farmers and the broader society. To accomplish this, all aspects of agriculture must comply with sustainability [49,50]. Agriculture 5.0 also incorporates green concepts and the widespread use of renewable energy and energy harvesting technologies in order to reduce the overall cost of agricultural practices while benefiting the environment. Although there is increasing interest in these technologies, widespread adoption has not yet been achieved. Last but not least, one of the key objectives of Agriculture 5.0 is to ensure that farmers, suppliers, and other directly involved parties receive accountable and transparent security services. In addition, providing irreversible records of the process from farm to store aids in building trust between consumers and sellers of agricultural products [51].

In conclusion, this new concept of smart agriculture, which aims to accomplish more with less, will be crucial in the coming years because it satisfies the need to provide people with the agricultural products they require while simultaneously increasing production sustainably and protecting the environment. The employment of sophisticated technology in agriculture, which will provide vast information on environmental conditions, crop health, and soil conditions and permit the precise application of plant protection treatments, is a rational response to these challenges [52].

3. 6G-IoT: New Technologies and Emerging Services

Following the revolution brought about by the convergence of IoT applications and 5G network technology, 6G is expected to outperform its predecessor in many aspects, thereby enhancing both our daily lives and business productivity [53]. Figure 3 depicts the evolution of wireless communications over time, beginning with 1G communications developed in the 1980s and ending with 6G communications expected to be completed in the 2030s. As shown in the figure, 6G is expected to provide all of the features offered by previous network generations, as well as some new ones, such as full network coverage, the development of massive IoT and mobile applications using AI, improved satellite communications, and the development of fully autonomous systems [54].

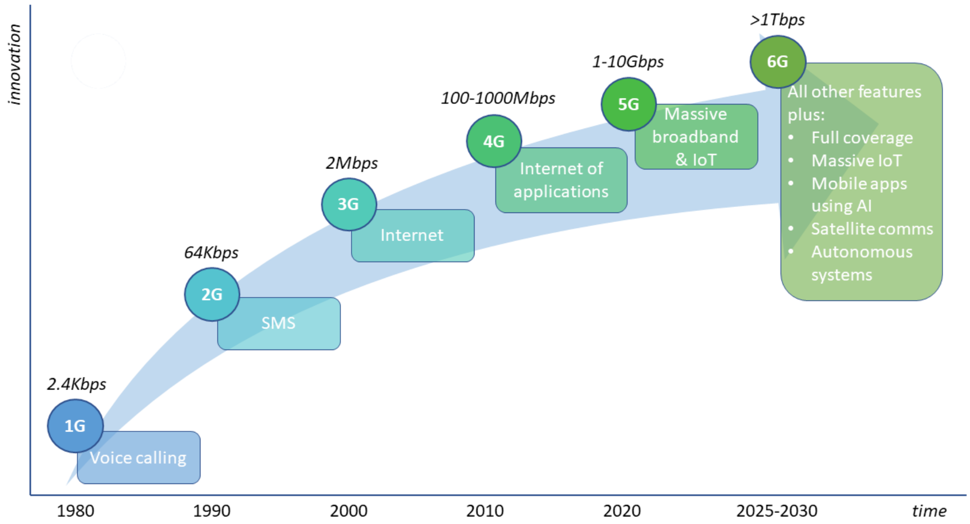

Figure 3. The evolution of wireless communications toward future 6G networks and applications.

In this context, 6G networking combines current and emerging technologies from the physical to the application network levels, creating a fully digitized and unified interface among users, services, computers, sensors, and smart objects in response to the new era's challenges [55]. In the areas of mobile broadband, end-to-end latency, geographical coverage, and mass connectivity, new horizons are opening, setting the foundation for the next generation of the Internet of Things.

The 6th Generation of the Internet of Things (6G-IoT) is anticipated to address critical issues involving massively reliable and ultra-low-latency communication, efficient use of communication protocols, and extensive IoT network geographic coverage. Moreover, with the advent of AI, devices are becoming more sophisticated and, in conjunction with their increased computing capabilities, are able to interact actively with the network, as opposed to merely transmitting data [1]. Consequently, it is anticipated that the 6G-IoT framework will provide efficient solutions for industrial IoT, smart cities, and remote applications, which will have a significant impact on the next generation of smart agriculture [16]. The essential technologies that will make it possible to meet the 6G-IoT requirements and enable Agriculture 5.0 are depicted in Figure 4 and described in the sections that follow.

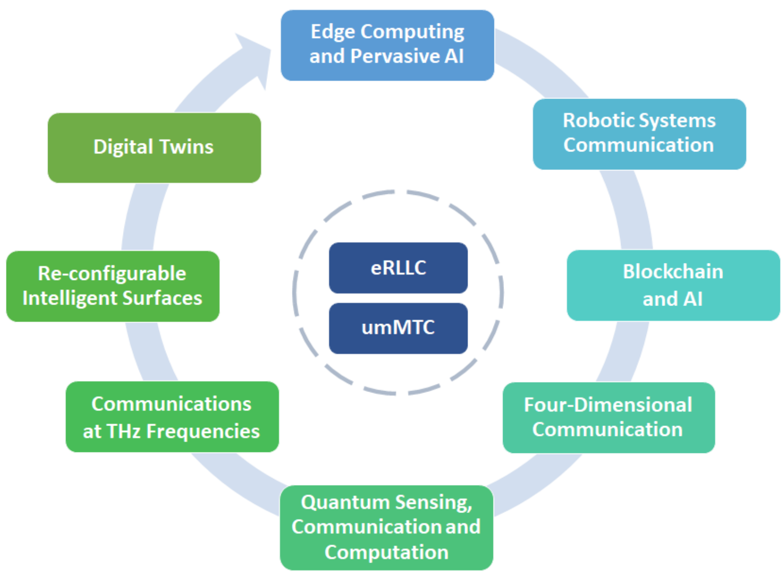

Figure 4. 6G-IoT enabling technologies in Agriculture 5.0.

3.1. Edge Computing and Pervasive Artificial Intelligence

Digital network devices, even those at the network's edge, have increasingly sophisticated computing capabilities. Therefore, we can utilize their computing power to assist with and, under certain conditions, optimize network performance [56,57]. Moreover, with the advent of AI, these devices will be able to extract information and expertise from the data they communicate with other entities on the network, identifying and categorizing services using learning models. Edge AI applications have emerged as a significant area of research, demonstrating their effectiveness in a variety of agricultural applications. For instance, cutting-edge computer vision methods utilizing deep learning can facilitate the extraction of navigation lines in intricate farmland environments for field robots [58]. Moreover, the integration of lightweight neural networks and edge computing enables real-time crop detection by harvesting robots [59].

The future of edge AI also involves a shift in the traditional approach of training models on powerful servers and then deploying them to edge devices. With the advent of federated learning (FL), the training process becomes decentralized, and the training data are stored on the edge devices where they originated [16]. In this approach, edge devices contribute to the training process by sending local model updates computed using their own data to a central server. The central server aggregates updates from multiple devices, modifies the global model, and then distributes the updated version to the edge devices. This iterative procedure continues until the global model reaches the desired performance level. As a result, the need for data transmission from the network's edge to the cloud is significantly reduced, leading to increased security and an accelerated training process [60,61].

Overall, edge computing and edge AI offer the benefits of local data processing, which reduces the need to send data to the cloud. This, in turn, helps to alleviate the traffic load on the backbone network. However, it is important to note that edge computing and edge AI cannot be universally applied to all deployment scenarios. They are primarily designed to provide immediate responses for real-time applications, such as navigation, coordination, and collaboration of autonomous vehicles and robots in farming operations. On the other hand, they are not well-suited for data-intensive tasks like large-scale analytics, high-resolution image processing, and augmented reality applications. Consequently, for complex tasks that require significant computational resources, it is still necessary to transmit data to the cloud. The extent to which edge computing and edge AI can reduce the need for communication with the cloud is dependent on the requirements of the specific application, the nature of the data, and the capabilities of the edge device.

3.2. Blockchain and Artificial Intelligence

Blockchain technology enables the creation of a distributed trust system. In fact, blockchain provides the same level of trust as traditional written contractual agreements due to its distributed and secure method of storing, managing, and transferring information and executing electronic transactions [62]. Specifically, the term blockchain refers to a public or private distributed ledger in which electronic transactions or data are connected in linked blocks of data. That renders them practically immune to malicious modifications due to a method that encrypts and hashes the block's information in an irreversible manner (one-way encryption) [62].

While blockchain is extremely useful in order to provide security in the distributed IoT environment, its use will be further enhanced with a combination of artificial intelligence methods [63]. The use of blockchain's digital record to track the rationale behind AI predictions and thus enable people to trust them will be a big benefit of the AI–blockchain combination in 6G systems. In addition, adopting blockchain technology for archiving and distributing AI learning models would provide an audit record, which would enhance security. Blockchain also facilitates the development of AI by granting it access to vast amounts of verifiable data, thereby enhancing the reliability of the decisions it makes [64].

3.3. Four-Dimensional Communication

Geographical coverage will exceed current boundaries, and communication will occur in four dimensions: on the ground, underwater or underground, in the air, and in space. Thus, a unified communication environment will be formed in which connectivity and services will be uninterruptedly provided by 6G-IoT [46]. Unmanned Aerial Vehicles (UAVs) and satellites are the key enabling technologies that will make this scenario feasible. Satellites provide wireless coverage in various earth orbits, including low (LEO), medium (MEO), and geostationary (GEO) earth orbits, thereby enhancing the current terrestrial telecommunications infrastructure and enabling the efficient network coverage of rural, remote, and geographically isolated areas [65]. Furthermore, new satellite systems in Very Low Earth Orbit (VLEO) will be developed, which will provide considerable advantages over traditional satellite systems, such as reduced satellite size and improved energy efficiency. VLEO systems also offer lower signal path losses and reduced latency communications, making them ideal for telecommunications applications [46].

In the airborne networking scenario, UAVs will be utilized as relays or even as mobile base stations in the event that a portion of the terrestrial network is compromised or destroyed during an emergency situation [66]. Additionally, they can be combined with satellite systems, forming a hybrid non-terrestrial network with advanced capabilities [47]. In addition, communications between submarines and specialized equipment for various ocean life monitoring services will be feasible in the underwater sector thanks to transponders linked to the terrestrial infrastructure. Following the concept of four-dimensional communication, underground sensors or devices embedded in the soil can also be employed in order to collect data on various parameters like moisture levels and nutrient content. In both cases, the main research challenge is to mitigate the increased signal attenuation caused by soil or water layer interference on the transmission path. This, in turn, impacts network topology, as there is a tradeoff between the energy consumption and communication range of underground/underwater sensor nodes. Thus, in this context, new technologies, such as the Internet of Underground Things (IoUT) [67], Wireless Underground Sensor Networks (WUSNs) [68], and Internet of Underwater Things (IoWTs) [69], are gradually advancing. Consequently, the enhanced monitoring, analysis, and prediction services that Agriculture 5.0 will offer will be substantially aided by the global continuous connectivity and reliable low-latency communication of 6G-IoT Non-Terrestrial Networks (NTNs) [38,70].

3.4. Quantum Sensing, Communication, and Computation

Quantum technology has been proposed for future networks as a promising technology capable of delivering super-high data transmission rates and significantly enhanced security [13,54]. The fundamental concepts of quantum mechanics are based on the superposition principle, which asserts that until a quantum system is measured, it can exist in multiple states simultaneously. Consequently, the quantum supercomputers of the future will not process information bits but rather quantum bits (i.e., qubits) that can be in a coherent superposition of both one and zero states. Quantum technology, which includes quantum sensing, quantum communication, and quantum computation, is expected to have a substantial impact on the design of future networked computing systems [16].

Many elementary quantum systems, including atomic spin systems, NV (nitrogen-vacancy) center ensembles, and trapped ions, can serve as quantum sensors [71]. Due to the extreme sensitivity of quantum states to even the smallest changes, these sensors have a higher sensitivity than conventional sensors, and they have the potential for more precise monitoring of physical parameters such as electromagnetic fields and temperature.

Moreover, quantum communication is expected to revolutionize data transmission by utilizing the principles of quantum mechanics to ensure a secure and tamper-proof exchange of information. Quantum communication protocols have the ability to detect any interception or eavesdropping attempts, as the act of measuring quantum states disrupts their delicate properties. Furthermore, the implementation of quantum key distribution

(QKD), a method that leverages quantum mechanics for securely creating and exchanging encryption keys between two parties, will further enhance the protection of sensitive agricultural data. Consequently, valuable data, including crop yields, market predictions, and sensor-derived information from the field, will be safeguarded, ensuring their integrity, confidentiality, and authenticity while mitigating the risks associated with unauthorized access and manipulation [72,73]. In addition to its applications in computer communication and high-precision sensing, the academic community has shown interest in quantum computing. The main advantage of quantum computing is quantum parallelism, which enables quantum computers to simultaneously compute multiple outputs of a function, exceeding the capabilities of classical computing. Quantum computing is anticipated to be widely utilized for accelerating the analysis of big data sets and minimizing the training phase of Machine Learning (ML) algorithms. By going beyond classical binary computing, quantum computing can significantly reduce the training and execution times of machine learning algorithms, making them suitable for real-time, computationally demanding applications. The new field of research that emerges from the combination of quantum computing with machine learning is referred to as Quantum Machine Learning (QML) [74,75].

3.5. Terahertz Communications

To address the spectrum and capacity shortage below 6 GHz, the adoption of higher frequency bands has already been standardized in 5G networks, primarily for frequencies between 24 and 48 GHz, permitting the development of new very-high-speed services. Future 6G networks are anticipated to employ frequencies over 100 GHz in the THz frequency range (0.1 to 10 THz) [76]. It is anticipated that systems designed to make use of these ultra-high-frequency bands will feature extremely low latency and enormously high data rates. As the number of IoT devices and the volume of generated data continue to increase, the development of high-bandwidth and low-latency communication links will provide a foundation for scalability, accommodating the growing demands of data transmission and processing.

However, THz communication systems are still in their infancy, and while some of their challenges are similar to those of 5G mm-wave systems, many others are unique and require the development of novel technological solutions [76,77]. Consequently, innovative transceiver designs, transmission techniques, and communication protocols must be devised to meet the requirements of 6G THz systems. Once these challenges are sufficiently addressed, the THz communication systems will be able to support new applications with higher requirements and, in light of next-generation agriculture, will be able to enable ultra-high-precision agriculture services [78,79]. These services are expected, for example, to offer plant-level data and therefore unparalleled accuracy in targeting and treating even individual plants, which will massively reduce chemical use. Clearly, such approaches necessitate extremely demanding real-time, ultra-high-resolution field monitoring, which could be efficiently supported by future 6G THz systems [76].

3.6. Reconfigurable Intelligent Surfaces

Despite the fact that current 5G networks are more energy- and spectrum-efficient than their predecessors, it is anticipated that future 6G networks will utilize the innovative technology of Reconfigurable Intelligent Surfaces (RIS) to further enhance energy and spectrum efficiency [80]. The aim of RIS technology is to transform the wireless environment dynamically, thereby overcoming the stochastic nature of the propagation channel. In this sense, the wireless environment could be an additional variable in network design with specific, measurable, and modifiable properties. In addition, the use of RIS in THz communications could be more challenging but extremely promising in reducing the high propagation attenuation of ultra-high-frequency signals.

Consequently, the employment of RIS technology could be incredibly useful in a variety of Agriculture 5.0 scenarios, as it could extend the monitoring range (i.e., the coverage area) and reduce the amount of power consumed, both of which are essential for IoT systems [81]. RIS can also be combined with wireless power transfer systems to focus transmitted energy on the intended sensors, enhancing the overall efficiency of the procedure [82]. Additionally, RIS could be integrated with Simultaneous Wireless Information and Power Transfer (SWIPT) systems, allowing the end device to concurrently harvest energy and decode information [83]. Therefore, it is anticipated that RIS technology will be an essential component for efficiently powering edge IoT devices in 6G-IoT systems, thereby providing a number of benefits for Agriculture 5.0 deployment scenarios.

3.7. Digital Twin Technology

With the use of digital twin technology, engineers can create virtual replicas of physical objects or even systems to test and validate concepts before production. A digital twin can also be used in real time and, by regularly synchronizing and exchanging data with its real counterpart, it could greatly facilitate both its maintenance as well as its integration with other systems [76]. In addition, digital twins can be utilized in diagnostic or prognostic procedures employing historical data and leveraging big data and artificial intelligence technology [84]. The necessity to evaluate novel concepts, designs, and services is what motivates the deployment of digital twins in sixth generation IoT networks. As a result, the technology of digital twins is now included in 6G-IoT research and standardization processes.

The use of digital twins to improve urban aquaponics farming is detailed in [85]. Aquaponics, which employs hydroponic farming principles, aims to create closed nutrient cycle systems that permit the concurrent cultivation of plants and fish. In this project, digital twin technology was used to provide an aquaponics system with the capacity to adapt to and foresee potential problems. Additionally, the study presented in [86] that uses digital twins, IoT, and big data may have accurately predicted future greenhouse conditions, which can assist in securing the planet's sustainability in the future. Even though using digital twin technology has many advantages, there are still a number of issues that need to be addressed as part of the 6G-IoT research and standardization process, particularly with regard to security issues and the accuracy with which digital and real-world systems can be matched [87].

3.8. Sustainable End-to-End Network Architecture: The Role of Green Technologies

Sustainability is a primary consideration for 6G networks, with an emphasis on the reduction of energy consumption and the employment of green technologies. The objective is to design an end-to-end network architecture that operates efficiently while minimizing its environmental impact. Consequently, the concept of energy optimization is not restricted to a single 6G network component. Instead, it incorporates the entire network architecture with the objective of reducing energy consumption and maximizing the use of renewable energy sources [88].

In this context, it is anticipated that 6G networks will employ artificial intelligence to optimize energy consumption via intelligent power management processes. By employing AI and ML algorithms to monitor and optimize energy usage, it will be possible to reduce the energy consumption of 6G networks without impacting their performance [89]. This will not only reduce the ecological footprint of 6G networks, but it will also help extend the battery life of wireless IoT devices. Furthermore, it is anticipated that energy-efficient hardware will be one of the most significant green innovations utilized by 6G-IoT. As the demand for wireless communication increases, so does the energy requirement to power wireless devices. Through the use of energy-efficient hardware, it is possible to reduce the amount of energy required for data transmission, thereby reducing the carbon footprint of 6G networks.

Energy harvesting is also an essential technology that is expected to be employed in 6G networks. This technology captures and transforms ambient energy sources like heat, light, and motion into electrical energy and is typically used for powering low-power devices or sensors in remote or inaccessible areas. Moreover, it is anticipated that

6G networks will make extensive use of renewable energy sources such as solar, wind, biomass, and hydroelectric power, which are becoming increasingly efficient and cost-effective. By utilizing renewable energy sources to power 6G networks, it will be possible to decrease their reliance on fossil fuels and, in turn, their carbon emissions [90–92].

3.9. Anticipated Advancements in 6G Services: umMTC and eRLLC

In order to support massive Machine-Type Communication (mMTC), Ultra-Reliable Low-Latency Communication (URLLC), and enhanced Mobile Broadband (eMBB) in 5G systems, the 3rd Generation Partnership Project (3GPP) has standardized a number of technical advancements, starting with release 16's 5G New Radio (NR) deployments [93,94]. It is anticipated that after release 17, subsequent releases (releases 18, 19, and 20) will provide significant technological advances toward 5G Advanced and 6G. Specifically, 3GPP Release 17 targets existing use cases, such as mobile broadband and industrial automation, and aims to improve 5G system performance by enabling new use cases and providing ubiquitous connectivity for a variety of use case scenarios. Releases 18, 19, and 20 will usher in the era of 5G Advanced, where artificial intelligence, augmented reality, and NTN integration will be further enhanced [47]. Thus, the prerequisites for the creation of the next generation of networks will be satisfied, and it is predicted that the initial specifications for 6G networks will be released in 2027 [65,95].

It is anticipated that 5G network services focused on massive connectivity and reliable low-latency communication, especially in IoT environments, will continue to advance along this path of technological innovation. Therefore, it is anticipated that mMTC and URLLC services will evolve into umMTC (ultra-massive Machine-Type Communication) and eRLLC (extremely Reliable Low-Latency Communication), respectively [54,77,96]. Regarding umMTC, it is expected that it will be capable of supporting a density of over one million IoT connections per square kilometer. Given the exponential growth of IoT connections in industrial complexes, smart city environments, as well as semi-urban and remote rural areas, it is predicted that numerous umMTC services will emerge, although their characteristics (e.g., bulk, critical, scalable, and zero-energy MTC) and consequently their requirements will vary considerably [97]. 6G will also enable the use of eRLLC services in a significant range of Industry 4.0 and beyond applications, including the ubiquitous use of robots, UAVs, and new Human–Machine Interfaces (HMIs) in manufacturing and autonomous driving, as well as in next-generation agriculture [38].

As shown in Table 1, which compares the characteristics of 5G-IoT and 6G-IoT, it is anticipated that 6G-IoT will provide a significant increase in throughput and a corresponding decrease in latency.

Table 1. Comparison between the 5G-IoT and 6G-IoT requirements.

Requirements	5G-IoT	6G-IoT
Throughput (Gbps)	20	100
Latency (ms)	1	[0.01–0.1]
Energy Efficiency	×1000 of 4G	×10 of 5G
Network Coverage (global %)	70	99
Spectral Efficiency (bps/Hz)	30	100
Massive Connectivity (devices/km^2)	10^6	10^7
NTN Integration	Partially	Fully (Satellites & UAVs)
AI	Partially	Fully

In addition, a quite substantial improvement in energy and spectrum efficiency is anticipated. It is also projected that network coverage will expand to 99% on a worldwide scale, which can be attributed to the full integration of terrestrial and non-terrestrial networks. A tenfold rise in the density of connected devices per square kilometer is also expected, while at the same time edge network devices will support pervasive AI services [55].

4. The Future of Farming: 6G-IoT Applications in Agriculture 5.0

Agriculture 5.0 stands to benefit greatly from the development of 6G wireless networks, which are anticipated to increase network coverage, boost data rate, and decrease latency. 6G networking will serve as a stepping stone for enhancing IoT sensor connectivity, paving the way for revolutionary new smart agricultural solutions [98]. In Figure 5, there are several critical areas in which Agriculture 5.0 can gain significant advantages by implementing 6G-IoT technology. The adoption of 6G networks can considerably facilitate the deployment of smart agricultural applications. These applications include real-time crop monitoring, virtual plant disease assessment, predictive crop maintenance, AI-based learning methods and prediction models, augmented reality applications, and dependable and decentralized farming operations. The following sections will discuss the impact of 6G networks on these smart agricultural applications.

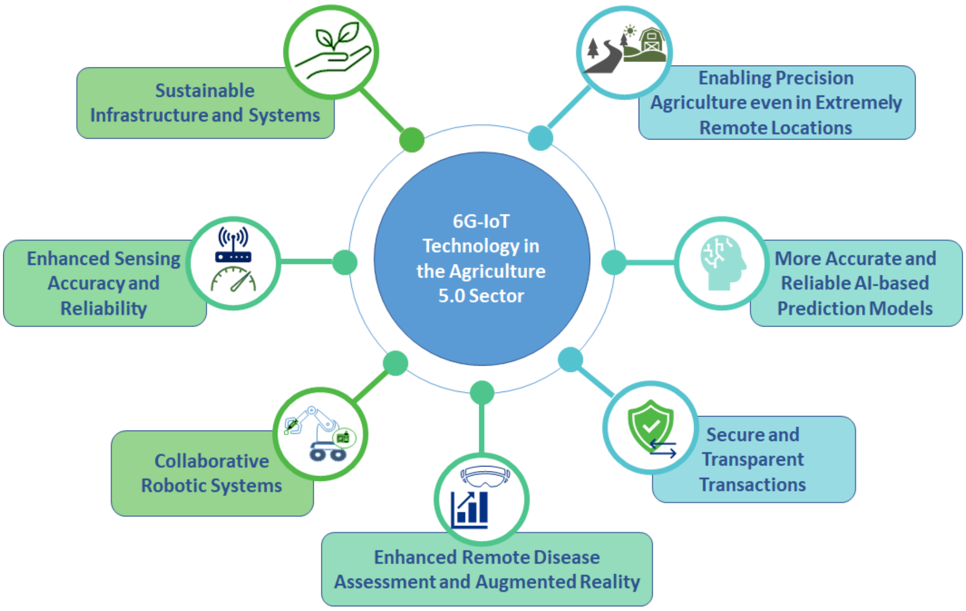

Figure 5. Applications of 6G-IoT in Agriculture 5.0.

4.1. Enhancing Sensing Accuracy and Reliability

A plethora of smart agricultural applications are currently presented in the relevant scientific literature, including smart irrigation systems [99], crop and weather monitoring [100,101], livestock management [102], UAV-based field monitoring, and greenhouse automation [103,104]. Nevertheless, the effectiveness of these applications is limited, as they typically employ a relatively small number of wireless sensors to collect environmental data such as air temperature, relative humidity, and soil moisture. With the advent of 6G-IoT wireless communications, however, there is the potential for significant improvements in the effectiveness and efficiency of these applications. 6G-IoT will allow for the connection of a vast number of sensors to a single cell tower (i.e., umMTC), enabling farmers to install more sensors and receive more accurate and detailed information even on a plant-by-plant basis [105,106].

Additionally, the utilization of quantum sensing technology can contribute significantly to this objective. Quantum sensors, relying on highly sensitive quantum systems, offer greater sensitivity compared to conventional sensors. Thus, two recent research studies [107,108] propose the use of quantum sensors for the precise measurement of photosynthetically active radiation (PAR), which is regarded as one of the most important environmental metrics required to evaluate plant photosynthesis. Furthermore, in [109], the authors employed devices equipped with multiple quantum sensors in order to precisely measure PAR as part of a cost-effective UAV-based thermal system to generate predicted maps of leaf water potential (LWP). Moreover, quantum sensors can be employed to accurately measure pH levels and ions, enabling the precise assessment of essential nutrients such as nitrogen, phosphorus, and potassium, which facilitates the implementation of precise fertilization strategies. Additionally, the deployment of multiple quantum sensors in a network allows for the utilization of inter-sensor correlations, further enhancing the overall sensing capabilities of the system [110]. Moreover, [111] investigates the use of quantum dots, which are typically nanoscale semiconductor particles or structures with unique quantum mechanical properties due to their size, for the production of nanobiosensors that are able to detect distinct targets in plants, such as pathogens, nutrients, and pesticides.

Using blockchain technology, all sensor measurements can be recorded on a tamper-resistant, decentralized ledger, enabling secure, transparent, and reliable record-keeping [112]. The collected data can then be analyzed using AI-based technologies such as machine learning algorithms, which can efficiently process and analyze the data to extract valuable insights, patterns, and trends. By employing quantum sensing and computing, blockchain, and AI, farmers will be able to acquire more precise and comprehensive data, thereby enhancing the effectiveness and productivity of smart agriculture.

4.2. Transforming Farming with Collaborative Robotic Systems

Future agricultural IoT systems will be based on robotic communication, which is essential for automating processes. In the smart agriculture industry, the use of collaborative production robots to achieve single or multiple objectives is already widespread and is expected to further increase in the future [16]. In Agriculture 5.0, these AI-based robots will perform a variety of tasks, including identifying patterns of anomalies and diseases across the plant, seed, soil, and weed spectrum and administering treatments to preserve the health and quality of plants [113,114].

As part of the Agriculture 5.0 framework, it is anticipated that an increased number of robotic systems will be employed and equipped with ultra-high-precision (UHP) sensors [98]. This will result in a nearly constant flow of a large volume of time-sensitive information between the management system and the involved robotic systems. Therefore, future agricultural collaborative robotic systems [115] will rely on umMTC and eRLLC 6G services, which will enable autonomous machinery to operate safely and efficiently in the field, thereby reducing labor costs and increasing productivity. The ultra-low-latency communication will also enable faster response times to unanticipated events in the field, thereby enhancing system resilience and reducing downtime. Furthermore, by creating digital twins of farm machinery and equipment, farmers could monitor their performance and detect potential issues before they occur [87].

In summary, the 6G-IoT standard will pave the way for secure, reliable, and ultra-low-latency communication between robots and between robots and the management system, which is crucial to optimizing the operation of future collaborative robotic systems in Agriculture 5.0.

4.3. Enabling Precision Agriculture in Extremely Remote Locations

Smart agricultural systems are commonly established and operated in geographically remote regions. With the evolution of 5G technology, it is possible to provide satisfactory remote coverage and connectivity services by integrating terrestrial and satellite systems [116]. However, the emergence of Agriculture 5.0 presents new challenges due to its ultra-precise service requirements. Consequently, it is expected that 5G networks will face difficulties meeting these demands, especially in remote and isolated areas [47].

In the four-dimensional unified communication environment of 6G-IoT, however, novel technologies are anticipated to provide effective and dependable solutions for precision agriculture in extremely remote areas. In space, the advent of 6G VLEO satellite mega constellations will provide dense satellite swarms that will be able to cover even the most remote areas and provide low signal path loss and reduced communication latency [55]. Specifically, it is projected that 6G global coverage will be greater than 607×103 km^2, offering a peak throughput of up to 18 Gbps/km^2. In terrestrial networks, RIS technology could be used to enhance wireless backbone networks, which are typically used to connect remote agricultural areas, given that it can extend the range of wireless connections and conserve energy. Moreover, due to the fact that RIS can be combined with wireless power transfer systems or SWIPT systems, it can also be very useful for charging IoT devices in Agriculture 5.0 remote monitoring scenarios [83].

In the case of aerial networking, UAVs could be used as relays or even mobile wireless access points when part of the terrestrial network has been compromised or obliterated as a result of a natural disaster. UAVs are well-suited for this application due to their ease of shifting position and establishing a line-of-sight channel with ground devices, as well as their controllability [56]. Due to their low operating altitude, they are classified as a low amplitude platform (LAP), a category that will be supported by 6G standards. In addition, they may be combined with satellite systems to create a hybrid non-terrestrial network with enhanced capabilities, such as wider coverage, higher bandwidth, and more resilient communication connections [70].

4.4. More Accurate and Reliable AI-Based Applications

The use of AI in Agriculture 5.0 can lead to innovative applications such as autonomous farm robots and farming systems. Furthermore, this rather new field of research offers new possibilities for creating more robust smart agricultural applications, ranging from weather or crop yield prediction and forecasting [117,118] to video monitoring and remote crop diagnostics [112], thus fulfilling the basic requirements of Agriculture 5.0.

However, as stated in the preceding subsections, the introduction of 6G-IoT can significantly improve the measurement process in terms of the quantity and quality of measured data, as well as by providing greater coverage even in geographically remote areas. Gathering the proper field data is arguably the most critical aspect of designing an AI-based smart agricultural application, as this information can determine how well the final system will operate. Consequently, the employment of an AI-based analysis and prediction model will result in more accurate forecasts when it is able to harvest data from a much larger area of interest, taking into account a greater number of parameters, and having larger data sets. Furthermore, by harnessing the parallel processing ability of quantum computing, which is expected to deliver significantly increased processing speeds compared to traditional computing once fully developed, the time required for training and executing AI algorithms can be greatly reduced [74,75,119]. Several scientific studies have explored the use of quantum computing [120,121] and quantum-assisted machine learning [122,123] for various smart agriculture-related objectives. These objectives include optimizing data analysis and decision-making, specifically in areas such as production planning and insurance risk assessment, enhancing image processing techniques for disease diagnosis, as well as enhancing disease classification techniques. In addition, quantum computing enables the execution of complex simulations that can be used, for example, in forecasting and modeling weather patterns. Moreover, quantum-assisted machine learning techniques can be used to predict phenotypes from genomic data and facilitate drug discovery by identifying, validating, and characterizing biological targets that are effective against disease mechanisms.

In addition, the widespread integration of blockchain technology and AI will permit the development of trustworthy and accurate prediction models. The combination of blockchain and quantum communication will eliminate the possibility of data manipulation by ensuring that critical data such as meteorological conditions, agricultural yields, and soil quality are securely delivered, maintained, and verified on the blockchain network. Consequently, the combination of AI, quantum communication, and blockchain will ensure that AI models are trained with data that are both reliable and immune to malicious tampering [63,124]. Furthermore, with the development of 6G-IoT networks, computing power at the network's edge will increase considerably, enabling federated learning (FL), a technology that can exploit the increased processing capacity at the network's edge. FL enables the AI training data to remain locally, reducing the need to transmit sensitive information to the cloud. This strategy ensures that essential privacy and security concerns are addressed, as the data remain private and secure. Consequently, the use of FL in future 6G-IoT networks is expected to leverage the increased computing capacity at the edge while maintaining data privacy and security [60,125].

4.5. Enhanced Remote Disease Assessment and Augmented Reality

Remote disease assessment involves the use of optical sensors, which can be stationary or mobile, in order to provide live, high-definition video. Thus, domain experts such as agronomists and related professionals can provide their guidance without the need for a physical meeting with the farmer in a location that is quite often remote. The expert can simply retrieve the live feed from the field-deployed sensors in order to inspect it and propose appropriate solutions [126]. While this process typically falls within the capabilities of 5G systems, the deployment of 6G networks will allow it to be further exploited even in the most remote areas and in an energy-efficient manner. Furthermore, the 6G networking environment will also offer higher data rates and a higher quality of data, which can include, for example, low-latency hyperspectral video streaming the detection of specific materials, identification of chemical compositions, and analysis of fine-grained details that are not visible to the human eye, while at the same time ensuring the security of the communication links. The use of pervasive AI can also be advantageous for both security procedures and expert systems that can provide agriculture-specific advice [44].

Furthermore, augmented reality (AR) can aid farmers in numerous ways. AR is a technology that superimposes computer-generated images onto the real world, enhancing the objects and information in the user's view. Thus, AR can significantly improve field disease assessment and reduce the use of agrochemicals by facilitating accurate pest identification and detection of pest attacks and infections in early stages, as it can provide an immersive and visual representation of the pest's life cycle stages [127]. Thus, AR will facilitate the application of the appropriate treatment at the appropriate time, reducing the need for excessive agrochemical use.

Moreover, by combining digital information with a farmer's environment in real time, augmented reality is able to deliver useful information such as the condition of crops and machinery, weather updates, soil and water conditions, and AI-based plant disease diagnosis via smartphones or glasses, enabling farmers to make informed decisions [128,129]. In addition, AR agricultural applications will benefit from the secure, reliable, and low-latency connectivity of 6G networks. This will enable them to transfer data in real time without any lag that could cause motion sickness to the end-user and reduce the efficiency of the AR application. Finally, in education and knowledge sharing, AR can be used as an educational tool to train farmers and agricultural workers about pest identification, prevention methods, and organic farming practices [130,131].

4.6. Enabling Secure and Transparent Transactions

In the Agriculture 5.0 ecosystem, a decentralized system for secure transactions can be developed by combining the strengths of quantum communication, AI, digital twins, and blockchain technology with the 6G-IoT networking infrastructure [124]. In such a system, quantum communication, utilizing quantum mechanics principles, can provide tamper-proof communication channels, while the integration of quantum communication and blockchain facilitates efficient, accountable, and transparent transactions. Moreover, the additional employment of AI and digital twins enables timely identification of threats, enabling proactive measures to be taken.

In the context of social protection measures intended to mitigate the effects of natural disasters on farmers, agricultural insurance can utilize such decentralized systems to support a variety of security plans. Smart contracts are required to streamline processes and enable direct compensation to affected individuals or groups in order to increase the effectiveness of these plans. The need for third-party data evaluation can be eliminated by automating the collection of data on estimated losses. This will allow for a more precise assessment of damages and the prompt delivery of compensation, reducing the financial burden on affected farmers [51]. In addition, it is essential to point out that a decentralized blockchain network can provide permanent records of agricultural products' journey from point of production to point of sale [63]. This approach can assist in establishing a relationship of trust between the consumer and the producer, as well as providing opportunities and rewards to producers that utilize agricultural resources in a sustainable manner [132].

4.7. Sustainable Infrastructure and Systems

Smart agriculture will play a key role in both economic growth and global agricultural output under the new vision of Industry 5.0, which prioritizes reducing energy consumption and promoting sustainable practices. Although 5G networks have provided a more viable solution to environmental protection and energy efficiency challenges than 4G networks, the 2030 goals for a sustainable society have not yet been met, and further holistic solutions must be explored [77].

6G networks will provide a sustainable end-to-end network architecture, with essential green technologies such as energy harvesting and the utilization of renewable energy incorporated into their standards. Moreover, with the ubiquitous use of artificial intelligence, it will be feasible to dynamically monitor and control the end-to-end network in an agro-ecosystem in order to achieve both the desired performance and the overall dynamic management of energy consumption, embracing green principles. In accordance with the aims of Industry 5.0, it is anticipated that Agriculture 5.0 will be developed based on the 6G pillars and managed through sustainable practices [16].

Regarding the reduction of agricultural inputs, there has been a recent shift towards the use of nano-materials such as nano-fungicides, nano-fertilizers, and synthetic nano-chemicals as a sustainable method for treating and preventing plant diseases. This approach not only substantially improves effectiveness, but also reduces the release of toxic chemicals into the environment [42]. Examples of eco-friendly nano-fungicides include metal oxides such as Cu, TiO_2, and ZnO, as well as Ag-based nano-fungicides. These nano-fungicides have broad-spectrum antipathogenic activity and are highly effective with minimal administration [133,134]. By enhancing sensing accuracy and reliability as discussed in Section 4.1, enabling precision agriculture even in the most remote areas (Section 4.3), and employing secure AI-based data analysis (Section 4.4), 6G-IoT will allow for a timely and precise diagnosis to be made with ultra-high-precision even for each plant individually, allowing for the best course of action to be determined.

5. Conclusions: Meeting the Challenges of the Future with 6G-IoT

The Organization for Economic Co-operation and Development (OECD) and the Food and Agriculture Organization of the United Nations (FAO) collaborate on agricultural issues to provide analysis and policy recommendations to encourage equitable and sustainable agricultural growth. The OECD–FAO Agricultural Outlook report [135,136], which is produced by the two organizations jointly, is a resource for decision-makers, academics, and other stakeholders in the agriculture and food sectors.

Population and income growth, urbanization, and dietary shifts are expected to continue fueling the global demand for agricultural products, as indicated by this report. To address the challenges facing global agriculture and food systems, it is recommended to increase investment in agricultural research and development to improve productivity, promote sustainable agriculture practices, improve access to credit and insurance for smallholder farmers, invest in rural infrastructure, and promote trade policies that support sustainable and inclusive agriculture [135]. Therefore, based on these projections and recommendations, as well as our previous analysis of the future of agriculture, a new and demanding landscape is progressively emerging in which Agriculture 5.0 can provide adequate technological solutions to the issues that have been identified by OECD–FAO.

As we previously analyzed, the current generation of smart agricultural applications, which rely on a relatively small number of wireless sensors, have limitations in terms of accuracy and effectiveness. However, the development of 6G-IoT communication technologies can be the base on which the future of smart and sustainable agriculture can be built, as shown in Figure 6.

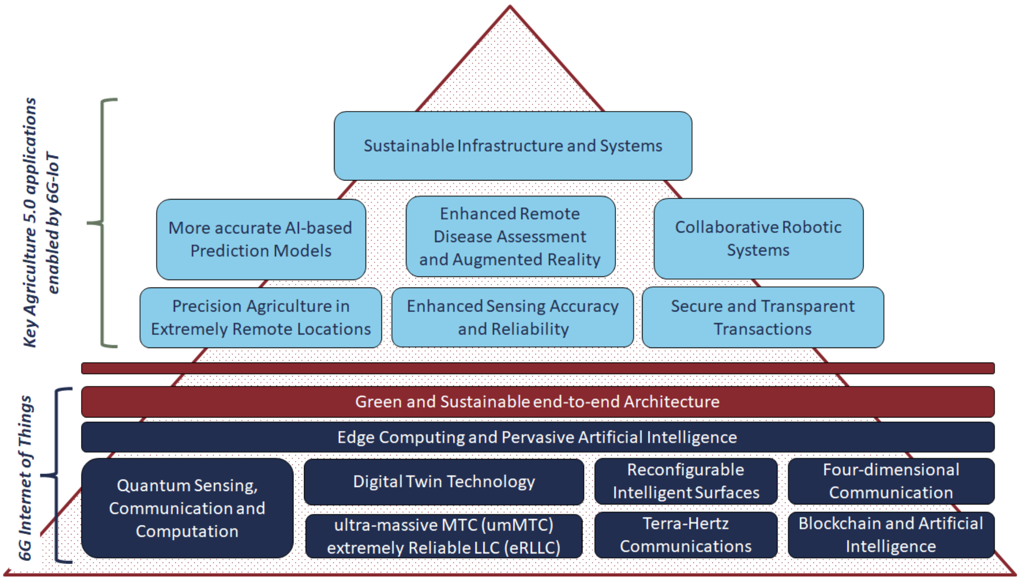

Figure 6. 6G-IoT as a basis for Agriculture 5.0.

6G-IoT technology will allow for the connection of a vast number of sensors, enabling farmers to collect more detailed information on a plant-by-plant basis. Quantum sensing technology, which can detect even the slightest changes in an agricultural system, will also contribute to this objective. With the use of blockchain technology, all sensor measurements can be recorded on a tamper-resistant, decentralized ledger, enabling secure, transparent, and reliable record-keeping. AI-based technologies, such as machine learning algorithms, can efficiently process and analyze the collected data to extract valuable insights, patterns, and trends.

In addition to enhanced sensing accuracy and reliability, the transformation of farming with collaborative robotic systems is another key aspect of smart agriculture. These AI-based robots will perform a variety of tasks, such as identifying patterns of anomalies and diseases and administering treatments to preserve the health and quality of plants. Future agricultural collaborative robotic systems will rely on umMTC and eRLLC 6G services, which will enable autonomous machinery to operate safely and efficiently in the field, thereby reducing labor costs and increasing productivity.

Finally, the use of 6G-IoT technology can enable precision agriculture in extremely remote locations. The advent of 6G VLEO satellite mega-constellations will provide dense satellite swarms that will cover even the most remote areas and provide low signal path loss and reduced communication latency. In terrestrial networks, RIS technology could be used to enhance wireless backbone networks, and UAVs could be used as relays or even mobile wireless access points when part of the terrestrial network has been compromised. In conclusion, the use of 6G-IoT technology will revolutionize smart agriculture by providing accurate data collection, advanced robotics, and precision agriculture in remote locations, making agriculture more efficient, sustainable, and cost-effective.

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