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Review

A survey on the 5G network and its impact on agriculture: Challenges and opportunities

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ABSTRACT

Over the next decade, the superfast 5G network will play a critical role in farming industries to improve the yields and quality of crops while using minimal labor. Smart and precision farming allows farmers to be more informed and productive. The advent of 5G will considerably change the nature of jobs in farming and agriculture. The internet of things (IoT)-based cloud computing service in the 5G network provides flexible and efficient solutions for smart farming. This will allow the automated operation of various unmanned agricultural machines for the plowing, planting, and management phases of crop farming and will ultimately achieve secure, reliable, environmentally friendly, and energy-efficient operations and enable unmanned farms. This paper provides a complete survey on 5G technology in the agricultural sector and discusses the need for and role of smart and precision farming; benefits of 5G; applications of 5G in precision farming such as real-time monitoring, virtual consultation and predictive maintenance, data analytics and cloud repositories; and future prospects.

1. Introduction

Agriculture is the primary source of livelihood and plays a vital role in most countries' economies. Agriculture is not only associated with crop production but also includes animal breeding and land cultivation to offer food, fiber, and medicine. Different types of agriculture are practiced in different regions across the world, focusing primarily on providing healthy food to feed the population worldwide. Agriculture is the main source of income for developing countries. It ensures food security for a country and produces material for industry. Modern farming started approximately in the 18th century, referred to as the British Agricultural Revolution, when in a short period, many improvements were made to farming, leading to a major yield increase and more efficient methods. A four-field system and selective cross-breeding program were implemented to increase crop size as well as yields, replacing the three-field crop rotation system. The first subsequent revolution in agriculture took place between 1900 and the 1930s, when mechanized agriculture allowed each farmer to produce enough for 26 people. This agricultural revolution brought techniques such as soil management and the advent of various new farming tools. After many decades, a second revolution, known as the Green Revolution, took place in the 1990s. Genetically modified crops that are pest resistant and need less water were introduced with the help of scientific advancements, allowing each farmer to feed 155 people. The second revolution promoted the use of mechanized tools in farming practices, increasing the rate of production as well as the quantity of crop yield. The third revolution, also described as a green revolution, was the phase when genetically modified crops began to be used by almost everyone, leading to greater produce output.

With the rapid growth in the world population (World Population Clock, 2020), as shown in Fig. 1, food production worldwide has to be increased rapidly. An enormous demand has to be served cost-effectively without wasting resources such as water and electricity. Food losses (Dora et al., 2020; Lipinski et al., 2016) during food production account for 32% in developing economies. Conventional farming practices lead to erratic production, overutilization of resources, and unrestrained production of wastes. To meet those demands, farmers need more sophisticated technology to produce more from limited labor and land. This is where automation comes in.

The smart farming/agriculture (Grogan, 2012) concept using modern technology is the solution to increase the quantity and quality of agricultural products with minimal loss and labor. Precision farming and

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information and communication technology (ICT)-focused agriculture paves the way for the fourth revolution. Smart agriculture also addresses the various challenges of food security, climate change, types of soil, water shortages, resource utilization, labor, etc. (Beuchelt and Badstue, 2013; Neufeldt et al., 2013; Lipper et al., 2014; Gilbert, 2011; Molden, 2013; Wallace, 2000; Steenwerth et al., 2014; Johnston et al., 2009; Bekele and Drake, 2003) using a communication network. The Internet of Things (IoT) includes sensors, robots and drones that are connected through the internet to function automatically and semiautomatically to perform multiple tasks and collect data aimed at improving productivity and predictability (Lee et al., 2013; Atzori et al., 2010; Ojha et al., 2015; Ray, 2017). Smart farming utilizes artificial intelligence (AI) techniques to detect soil conditions and to select crops for planting based on the type of soil, weather conditions, availability of water, etc. to detect diseases in plants at an earlier stage and to select and apply the corresponding pesticides to improve yield by using appropriate sensors (Infosys, 2018; Sadowski and Spachos, 2020; Khan et al., 2020; Kamilaris and Prenafeta-Boldú, 2018; Chen et al., 2002; Magomadov, 2019). The data captured by the sensors in the drones flying over the farms are processed and analyzed by deep learning algorithms using computers to identify plant issues. Each grain in a bowl of rice is a result of hard labor. With the help of these technologies, it is possible to make farming easier. To support the 4G mobile network, (Tong et al., 2019; Zhao et al., 2016; Payaswini and Manjaiah, 2014) provides an easy path to connect the devices for data transactions without traffic, loss or delay, which considerably reduces costs, labor, and time. The Business Insider Intelligence service estimates that by 2020, the number of agricultural IoT devices will reach 75 million installations, increasing 20% annually. According to the report "Smart Agriculture Market by agriculture type (precision farming, livestock, aquaculture, greenhouse), hardware (GPS, drones, sensors, RFID, LED grow lights), software, services, application, farm size, and geography - Global Forecast to 2025" (Smart Agriculture Market by Agriculture Type, 2020), smart agriculture is projected to grow from USD 13.8 billion in 2020 to USD 22.0 billion by 2025, at a CAGR of 9.8%. Though the 4G network offers high speed and good connectivity, it is not possible to interconnect all the devices used in smart forming in remote places with low installation/maintenance costs. After the introduction of the 5G mobile network and ultra-high-speed networks, this task is made simple for sharing the information/resources effectively. In this paper, how the application of the 5G network will change agricultural industries to increase productivity and its impact is discussed.

2. IoT in smart farming

For increased production capabilities and analytics, farmers and agricultural industries are shifting to the IoT. The IoT involves several types of sensors that are designed to perform various key tasks that push the future of farming to the next level. These sensors are deployed all over the field, allowing farmers to obtain detailed insight into various parameters of the soil, plants, weather, livestock, etc. using a smartphone over the internet. With IoT technology, farmers are provided with complete information at different levels of smart farming, such as soil analysis and mapping, irrigation, fertilizers and pesticides, disease detection, harvesting and yield prediction and monitoring (Adamchuk et al., 2004). Topographic maps of the agricultural land and the information on the types of resources available in the region are obtained by deploying agricultural drones as well as ground-based sensors. This approach also enables farmers to perform a comprehensive analysis of soil, such as the temperature, acidity, nutrient status, and other properties (Sureephong et al., 2017; Placidi et al., 2020; Zhang et al., 2017; Payero et al., 2017; Sanchez-Iborra et al., 2018). All these variables can be combined with the historical data along with the types of cropping performed earlier, fertilizers and pesticides applied, water level, etc., to detect the quality of the soil. Soil maps are digitally created and are useful for sowing different types of crops specifically engineered for soil-related parameters such as crop suitability and planting depth. There are also sensors available to directly monitor the texture of the soil, acidity, water absorption, etc., based on which various toolkits provide recommendations to avoid soil erosion, acidification, pollution, etc. Due to water scarcity, IoT-based irrigation is preferred over traditional irrigation methods. IoT-based water control systems allow a precise flow of water to fields, thus preventing water wastage (Harun et al., 2015; Feng, 2011; Gupta et al., 2020). The crop water stress index (CWSI) was developed to quantify stress and to overcome the effects of environmental parameters affecting plant temperature and stress (Alderfasi and Nielsen, 2001). Later, its calculation evolved to incorporate the crop canopy and surface temperature at different intervals. Multiple sensory data such as weather, satellite images, infrared thermometry, etc. are combined to calculate the CWSI to obtain the site-specific irrigation index (Khanal et al., 2017; Lu et al., 1997; Labbé et al., 2012). Variable-rate irrigation (VRI) addresses the need for optimizing the irrigation schedule with the help of sensory data (Hedley and Yule, 2009; Evans et al., 2013; Dukes and Perry, 2006). IoT-based devices are used to calculate the chemical composition of fertilizers and soil, such as the

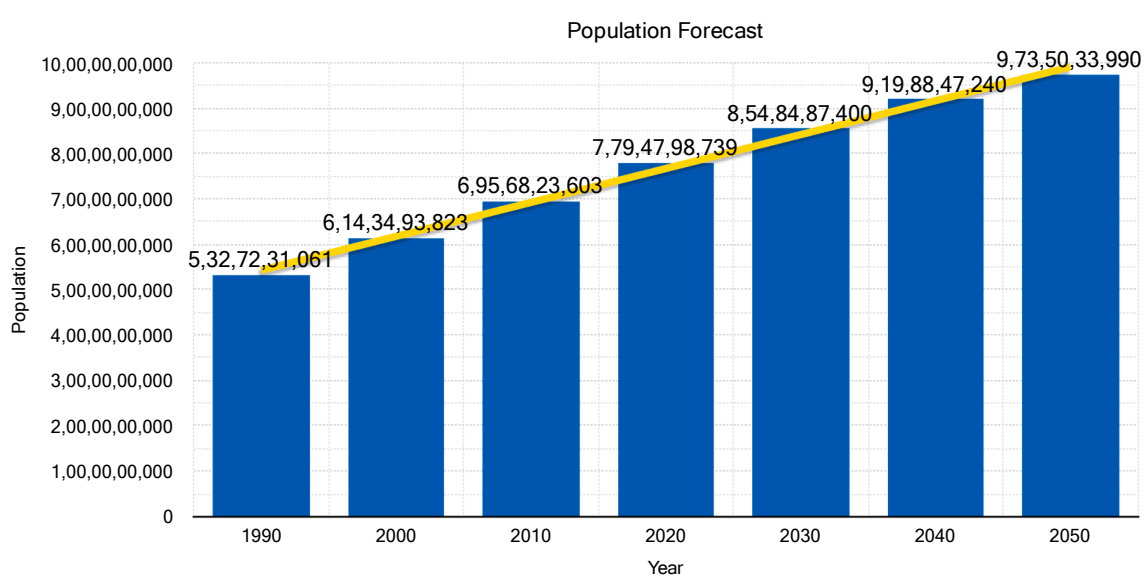

Fig. 1. World population forecast.

phosphorous, nitrogen, and potassium contents, as needed to ensure plant fertility. The data from the sensors, such as the nutrient level and weather, help determine the precise amount of fertilizers required for the growth of the crops, as excess levels affect the fertility level of the soil. Due to pests and diseases, an estimate of 20–40% of crops are lost annually according to a report by the Food and Agriculture Organization (FAO) (FAO, 2020). IoT devices such as robots, drones, and sensors are employed to detect pests and diseases, allowing precise usage of pesticides. By using these IoT-based devices, the overall cost and the factors affecting the environment are significantly reduced. There are several software apps, such as farmOS, that can utilize all the data from these IoT devices to provide information regarding the agricultural yield, quality of the harvests, crop yield estimation and live yield/harvest monitoring. All these data are uploaded to a custom server or web-based platform.

3. Challenges in the current generation of mobile networks

4G/3G/NB-IoT wireless network technology is used to provide connectivity between IoT-based smart devices for data sharing, precise assessment, accurate estimation, etc., in the agricultural field (Dahlman et al., 2011; Huang et al., 2012; Akyildiz et al., 2010; Hassebo et al., 2018). While the 3G/4G connectivity paradigm has shown great promise, there exist some limitations that can constrain the usage of the technology in the agricultural sector from its maximum potential. The operating area is one of the largest constraints. The existing wireless networks do not cover remote areas or parts of the city with several buildings. Facilitating quality of service (QoS) in 4G (Payaswini and Manjaiah, 2014; Tragos et al., 2008; Iera et al., 2005; Dell'Uomo and Scarrone, 2002) networks poses a significant challenge due to channel conditions, resource allocation, changing data rates, and handoff issues between heterogeneous networks. The multiple antennas and transmitters used in mobile devices in this network lead to poor battery life. Since many moving devices used in modern agricultural sectors, such as drones and robots, are battery powered, they cannot operate for long durations in remote crop fields. Several devices and a massive amount of research work on IoT devices for smart farming are steadily increasing and require more intelligence, speed, scalability, secure communication capabilities and processing power to perform heavy computational tasks and run loaded services. To achieve fast performance and low costs for IoT devices, ultralow latency combined with high connectivity is required. The current 4G network (LTE) cannot support such features because it allows IP-based packet switching connectivity only (Zhaogan et al., 2007; Martin et al., 2011). These limitations of the current generations of cellular networks will be overcome by transitioning to the next generation: 5G.

4. Rise of 5G

5G is the 5th generation mobile network technology; the formal standard was established in December 2017 by 3GPP to define the specification of the 5G network, and the second phase of 5G, 3GPP Release 16, is expected to be released shortly. The 5G mobile network makes use of a high-band spectrum (referred to as millimeter-wave) for very high speed and low latency (Andrews et al., 2014; Wang et al., 2014; Mitra and Agrawal, 2015; GSMA, 2018; 3GPP Release 16, 2020; Cudak et al., 2014; Rappaport et al., 2013). In addition to high data capacity and speeds faster than 10 Gbps, 5G also boasts the capacity to connect billions of devices because of its higher bandwidth. 5G will exceed the current 4G and 4G LTE standards by up to 100 times in regard to downloading and uploading speeds. This means that while it would normally take six minutes to download a two-hour movie on 4G, that same download would take less than four seconds on 5G. The International Telecommunication Union (ITU) develops technical standards for 5G (IMT-2020). The peak data rate per mobile station for uplink is 10 Gbps, and the downlink rate is 20 Gbps. However, for user calls, the actual upload speed is 50 Mbps, and the download speed is 100 Mbps. 5G can connect 1 million devices per square kilometer, and it is also supported when devices move at very high speeds (approximately 500 kmph). Another key benefit of 5G is delivering latency as low as 1 ms to overcome the lagging connection issues that exist in the current network generation (Yu et al., 2017; Sutton, 2018; Gupta and Jha, 2015; Huawei, 2018; Next Generation Mobile Networks Alliance 5G Initiative, 2015).

Since microwaves (MWs) are used as carriers in the 5G network, they cannot cover large regions. To provide seamless connectivity, the small-cell concept is introduced, in which small base stations are placed approximately 250 m apart throughout the coverage areas and can be extended to any extent. The associated small towers can be sited anywhere (lamp posts, trees, roofs, vehicle tops, etc.) to connect the larger extents. An illustration of how the 5G network is deployed (DotEcon Ltd and Axon Partners, 2018) in rural and urban areas, which may cover any range, is shown in Fig. 2. The massive multiple-input multiple-output (MIMO) technique (Jungnickel et al., 2014; Elijah et al., 2016) is employed here as in 4G by providing multiple transmitting and receiving antennas to enhance the capacity of the network, which is much greater than that of the 4G network. However, massive MIMO causes interference between the signals more easily. To overcome this problem, beamforming is used to maximize the efficiency of sending data. Beamforming is the ability of an antenna to send narrow beams of radio waves in the direction of the individual devices. Since 5G operates at very high (MW) operating frequencies, it supports very high bandwidth, which allows faster and larger data transaction. 5G can differentiate each device by using the cognitive radio technique and allocating dynamic channels for them; this facility is missing in the 4G network.

Benefits of 5G

- High capacity
- Decreased latency
- High connection density
- High throughput
- Improved spectral efficiency
- Seamless connectivity
- Wide coverage
- Increased network energy efficiency

Table 1 compares the 5G network with previous-generation mobile networks. Compared to the 3rd-generation mobile networks, 4G enabled high-definition video streaming and calling on the go. With increased congestion in the network, 4G has reached the technical speed limits across the spectrum. The latest 5G scenarios can be classified into three groups per ITU: enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultrareliable low latency communications (URLLC) (Popovski et al., 2018; Anand et al., 2020; Kasgari and Saad, 2018). In the case of eMBB, performance metrics of human-centric interactions such as the overall user experience are the primary goal, and in the case of mMTC, high connection density, minimal battery consumption, low cost and complexity are the primary goals. mMTC focuses on building and facility control, logistics, smart/precision agriculture, fleet management, etc. Hotspots (indoor/outdoor), wide-area coverage, and high speed are typical use cases. Fig. 3 depicts the global deployment status of the 5G network as of June 2020 (Ookla 5G Map, 2020). In 2018, 3GPP standardized the first 5G New Radio (NR) release (release 15), and 5G NR release 16 and release 17 were subsequently approved by ITU in IMT-2020. 5G NR utilizes two different frequency ranges: FR1 (below 6 GHz) for traditional communication network traffic and FR2 (20–60 GHz) for short-range and high data rate traffic (Dilli, 2020; Henry et al., 2020; Ghosh et al., 2019). The frequency band FR1 is mostly preferred over FR2 because it can travel farther and penetrate obstacles and has better coverage. As a large amount of spectrum is available in unlicensed bands, 5G NR utilizes an unlicensed spectrum to increase the data rates and capacity for 3GPP systems, which supports standalone operation. Currently, 5G mobile

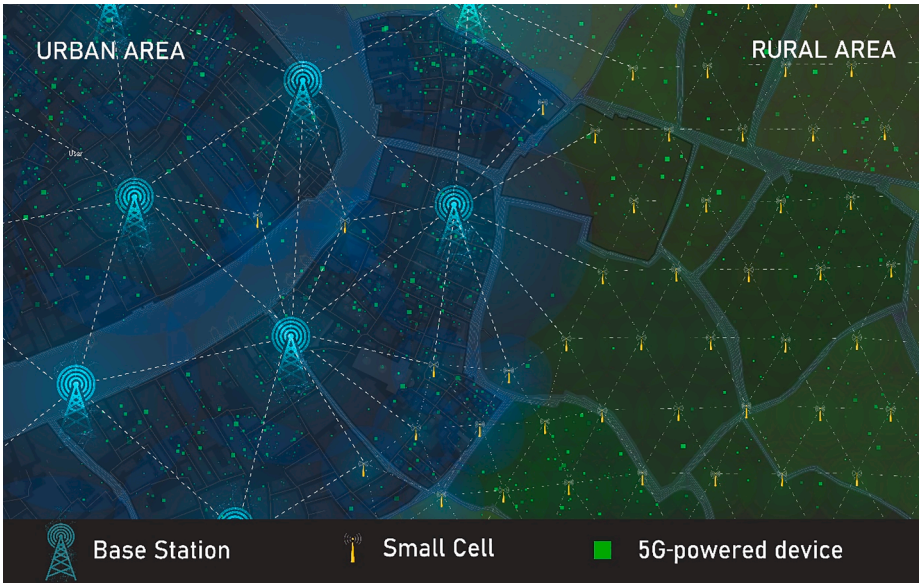

Fig. 2. 5G Cellular mobile network in urban and rural areas.

Table 1
Comparison of recent generations of mobile networks.

	2G	3G	4G	5G
Year of Introduction	1993	2001	2009	2018
Technology	GSM	WCDMA	LTE, WiMAX	MIMO, mmWaves
Access System	TDMA, CDMA	CDMA	CDMA	OFDM, BDMA
Switching Type	Circuit, packet	Circuit, packet	Packet	Packet
Network	PSTN	PSTN	Packet Network	Internet
Internet Service	Narrowband	Broadband	Ultrabroadband	Wireless World Wide Web
Bandwidth	25 MHz	25 MHz	150 MHz	30–300 GHz
Speed	64 Kbps	8 Mbps	300 Mbps	10–30 Gbps
Latency	300–1000 ms	100–500 ms	20–30 ms	1–10 ms
Mobility	60 km	100 km	200 km	500 km

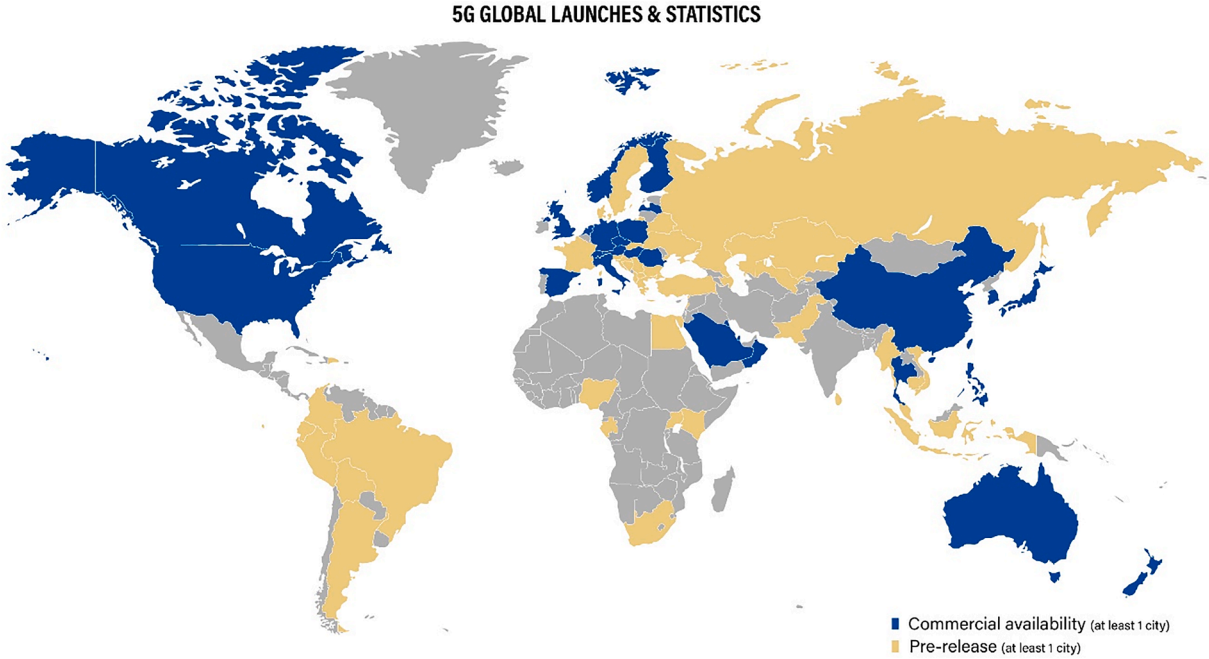

Fig. 3. Deployment status of the 5G mobile network as of June 2020.

networks are commercially available in 8719 cities and are expected to account for at least 1.3 billion global 5G connections by 2025.

Although 5G provides a significant improvement in bandwidth and speed, its limited coverage requires additional infrastructure. The 5G base station has a shorter range than that of the current generation, meaning that additional small base stations need to be installed. Thus, beaming with less power is achieved while handling larger data, and the installation cost of the base station is minimal, as it can be placed anywhere.

Currently, the penalty paid for the new 5G technology is the high infrastructure cost, end-user device cost, and service tariff. Initially, these costs may be high, but when it is implemented on a large scale, the cost will be reduced considerably. 5G network costs depend on the cost of the base station, throughput density, and recurrent interest rate (Bouras et al., 2017). By minimizing these expenses, the benefits of 5G technology should become more affordable to small-scale industries and the agricultural sector. Since 4G LTE and 5G networks use the same frequency spectrum, 5G technology has the potential to bring data costs even lower than the current 4G costs in the future. 5G is not standalone; instead, it uses updated radios and software on the 4G LTE. Thus, the existing 4G LTE devices can obtain much higher speed and reduced latency matching the current generation chipset's speed limits.

5. Application of 5G in agriculture

For agricultural IoT devices to function, a fast and reliable internet connection is required. The current generation of mobile networks is failing because of poor connectivity in rural regions, and even in the regions where high-speed connectivity is present, failure occurs due to enormous demands. A recent report found that almost 80% of rural areas, even in the United Kingdom, lie outside of the 4G range. In most countries, the current level of network availability in rural regions is insufficient (USDA, 2019). In addition, in some developed countries, there are multiple farms with a large number of IoT devices and machines that require a constant reliable high-speed internet connection to exchange a large amount of data, and the technologies of the current generation of mobile networks cannot cope with these demands. To fulfill these goals, many promising technologies, such as massive MIMO, network slicing, and smaller cells, are needed to provide reliable connectivity over a larger distance. Therefore, the 5G mobile network is well suited to support smart farming by enabling wide coverage, low energy consumption, low-cost devices, and high spectrum efficiency. In 2017, for the first time, the 5G Rural First project successfully planted and harvested a crop using autonomous tractors to sow seeds, drones to monitor crops, and machines to apply water, fertilizer, and pesticides. The whole process was performed without any laborers stepping into the field. In 2018, another project titled Hands-Free Hectare reported a successful harvest. With more advancements in technology, 5G is expected to promote precision farming. As 5G coverage expands, agricultural sector producers are highly beneficial, providing the ability to manage farms, livestock, etc. from the comfort of their home, thanks to their large capacity, high data speed, and low latency. 5G technology will aid in supporting IoT sensor connectivity to the next level, providing a path to drive groundbreaking innovation in smart farming components (Akpakwu et al., 2018; Modesta et al., 2019; Antony et al., 2020; Ayaz et al., 2019; Mavromoustakis et al.). The key areas where the deployment of a 5G mobile network is beneficial in the agricultural sector are shown in Fig. 4. The application of 5G in agriculture for unmanned aerial vehicles, real-time monitoring, virtual consultation and predictive maintenance, augmented reality and virtual reality, AI-powered robots, data analytics and cloud repositories are discussed in this section. 5G technology makes it much easier to deploy, monitor, and manage IoT devices and farms.

5.1. Unmanned aerial vehicles (UAVs)

Recently, UAVs/drones have been widely used in the agriculture industry. Applying drone technology, farms and agricultural enterprises can increase crop yields, save time, and make land management decisions that maximize long-term performance. These drones can be used for both aerial and ground-based tasks. Some key areas where the usage of drones is beneficial are listed below:

- Scouting land and crops
- Soil and field analysis
- Crop spraying
- Seed planting
- Livestock monitoring
- Health assessment
- Delivery of agricultural products

Drones employing several types of sensors, such as multispectral imaging, thermal infrared imaging, hyperspectral, and lidar, are used to scan a vast area for 3D mapping; counting plants; computing vegetation indices such as NDVI, CCCI, NDRE, MCARI, and CWSI; and capturing the health of the plants, soil temperature, and water levels (Ampatzidis et al., 2020; Gašparović et al., 2020; Liu et al., 2019; Chen et al., 2019). Drones are helpful in performing quick, efficient monitoring and auditing of livestock (Vayssade et al., 2019). Multiple drones can be deployed to perform multiple tasks over several acres of land, which can

Fig. 4. Application of 5G in the agricultural sector.

be expected to increase drone traffic. Usually, agricultural drones are used for low-altitude operations (below 120 m), and they use a specific radio connection or Wi-Fi; hence, there is a very limited range of 3–7 km with a large transmitting antenna. If the control over the UAV is lost for even a few seconds, especially due to travel beyond the visual line of sight (BVLOS) (Ivancic et al., 2019), the task being performed is interrupted, and emergency measures are activated to avoid losing the aircraft. Alternatively, for radio control, the use of the 4G network link appears to mitigate the distance issue, allowing a drone to fly several kilometers away from its controller (Lin et al., 2018). With an increase in drone usage, managing and identifying drones has become complex and tedious. The 5G mobile network is suitable for integration with drone traffic management to facilitate low-altitude drone communication to increase the security and safety of drone operations. Ubiquitous mobile broadband coverage will be achieved with the 5G network on the sky as well as the ground.

With 5G technology, farmers can fly a drone over a large distance either manually or through programmed checkpoints, and technically, the drone can be controlled from anywhere in the world (Faraci et al., 2018). The 5G cellular network allows farmers to receive real-time data; such as high-definition video streams, along with other essential sensory data and telemetry from drones faster and seamlessly compared to previous-generation mobile networks. The drones need not carry a large amount of processing power, and all the data can be sent to the cloud for processing at a faster rate with 5G technology. Multiple drones (Li et al., 2019; Wang et al., 2019; Feng et al., 2019; Razaak et al., 2019) can communicate with each other to provide synchronized autonomous flight over a geographical region and to perform multiple tasks with minimal data transmission loss and energy consumption, thus enabling prolonged airborne sensing time with cost-effective operation beyond the line of sight. A large amount of gathered data can be stored and analyzed for decision-making tasks. With widespread network coverage and stable communication of the 5G cellular network, a large number of autonomous drones can fly through the skies to deliver agricultural products at one's doorstep. Three key needs to link drones using 5G cellular data are unmanned aircraft system traffic management (UTM) (Aweiss et al., 2018; Johnson et al., 2017), flights beyond the line of sight and sensor data transmission. The 5G cellular network will integrate with drone traffic management systems to enhance the safety of drone operations and provide secure and high-quality connectivity to make BVLOS drone operations cost effective. Since a large amount of data is involved, a data connection with large and fast bandwidth is required, as offered by stable 5G network coverage.

5.2. Real-time monitoring

Wireless sensors that are connected to the internet can continuously monitor environmental conditions such as humidity, temperature, luminosity, and soil moisture (TongKe, 2013; Prathibha et al., 2017; Stočes et al., 2016; O'Grady and O'Hare, 2017; Baranwal et al., 2016; Zamora-Izquierdo et al., 2019; Ahmed et al., 2018). Based on any variation in these conditions, an automated corrective action can be initiated to maintain the normal conditions for plant growth. Agricultural data received from the respective sensors will be in different formats based on the required accuracy resolution and will require the appropriate interfaces for compatibility. Source application program interfaces (APIs), such as the Open Ag Data Alliance (OADA API, 2018) (OADA, 2020; Noel et al., 2018), are employed that use common storage platforms for data transactions. Many data repositories with different file formats are available from open sources for interoperability. An illustration of these IoT sensors for real-time monitoring is shown in Fig. 5.

Dedicated software packages such as SmartElement, Pycno for weather monitoring, Power BI, and Tableau for data analytics are employed to monitor several parameters of farming. There are several open-source platforms, such as Thingsboard and Openfarm, that perform data collection, visualization, device management, etc. Communication protocols play a major role in IoT-based intelligent farming to cover short-range or long-range distances of the land. For short ranges, ZigBee or Wi-Fi is used, whereas the LoRaWAN, Bluetooth, and LPWAN protocols in mobile communication networks are used over long ranges. To provide wide-area coverage, low power consumption,

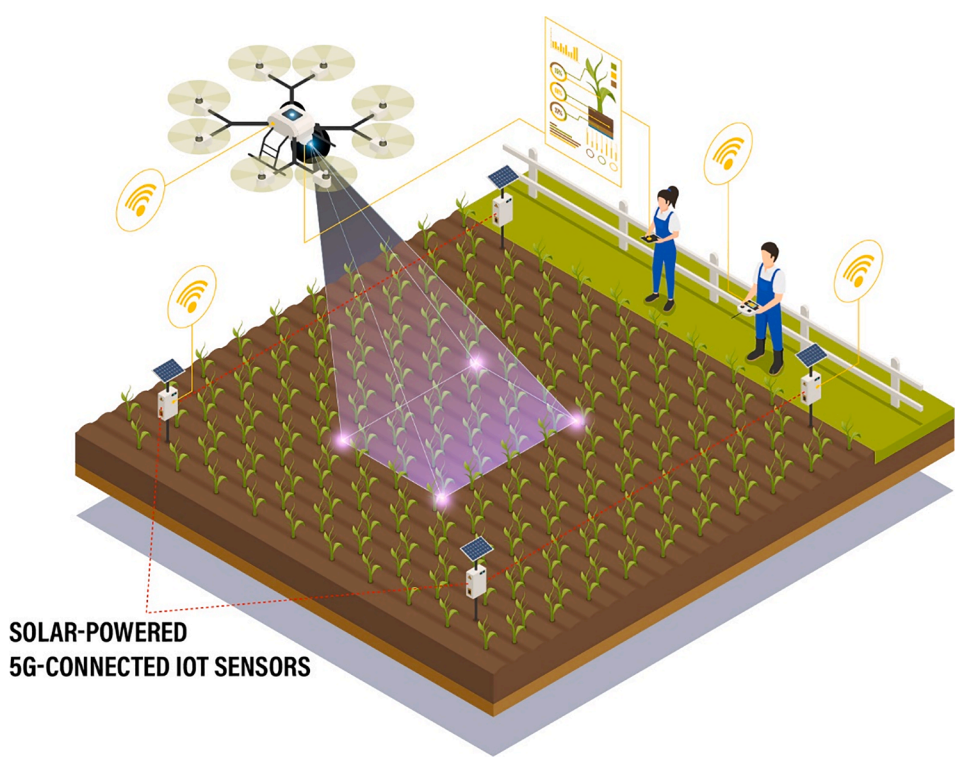

Fig. 5. Illustration of drones, real-time monitoring sensors and augmented reality at work.

high energy efficiency and high data rates, low power wide area (LPWA) technology can be used in 5G mobile networks (Sinha et al., 2017; Muteba et al., 2019; Mekki et al., 2019; Cho, 2019; Raza et al., 2017). The comparison of various protocols is shown in Table 2.

Long-term evolution machine-type communications (LTE-M) and narrowband IoT (NB-IoT) (GSMA, 2019; Hoglund et al., 2017; Ratasuk et al., 2016; Lauridsen et al., 2016; Miao et al., 2018) are paving the path to the future of 5G integration and will shape smart farming in the coming years. With a 5G cellular network, a massive number of sensors (1 million devices per square kilometer) can be connected to a single cellular tower, which will ultimately allow farmers to install more IoT sensors to perform all tasks more efficiently. The more IoT sensors that are used to track the data points, the higher the possibility of predicting and foreseeing various changes in the farms and making faster and better decisions. The sensors must have long-range connectivity and be power efficient, as most of the sensors are solar or battery powered. These IoT sensors take advantage of 5G technology's low power transmission and reliability (Oh and Shin, 2017; Yao and Bian, 2019). Hence, the lifetime of the sensors is increased sharply by transmitting data at lower energy and avoiding retransmission of data. As 5G NR supports adaptive bandwidth changing from lower bandwidth to higher bandwidth, it enhances network energy performance and reduces interference, while interworking and LTE coexistence make it possible to utilize existing cellular networks and can accommodate future evolution.

5.3. Virtual consultation and predictive maintenance

Agricultural domain experts or consultation services can attend to the needs of farmers through virtual consultation using high-definition (HD) streaming without the need for a physical meeting in the comfort of home. In addition to normal video conferencing, domain experts or consultation services can directly pull a live feed from real-time monitoring sensors or agricultural drones to obtain detailed insight into the situation and provide necessary solutions to farmers for the betterment of agricultural practice on time. Some services that are rendered by consultation services are crop consulting, environmental planning, precision agriculture, sampling soil, pest management, and farm animal health checkups. With 5G technology's fast data rates and low latency, multiple machines and equipment can be tracked and monitored in real time to monitor failing parts or fuel status in advance to provide repairs on time without any delay or halting of any preplanned tasks. 5G will add a new paradigm in maintenance known as advanced predictive maintenance by using multiple sensors fitted to various machines and equipment to measure a large number of different parameters in real time. With predictive maintenance, the farmer is informed about any upcoming issue and any failing parts based on feedback from different 5G-enabled sensors, allowing repairs to be scheduled in a timely manner and without halting any operation (Xu et al., 2012; Kanawaday and Sane, 2018; Compare et al., 2020). This can greatly reduce the unplanned downtime resulting from faulty equipment or machine breakdown.

5.4. Augmented reality and virtual reality

Advancements in technology and consumer-grade augmented reality (AR) and virtual reality (VR) kits can assist farmers in multiple ways. AR can provide assistive information such as the stats of crops, animals, machinery, drone live feed and telemetry, weather updates, soil, and water conditions, AI-powered disease detection for both plants and farm animals, pest detection, land examination, etc. through wearable glasses and smartphones (Xi et al., 2018; Katsaros and Keramopoulos, 2017; Caria et al., 2019; Garzón et al., 2020; Huuskonen and Oksanen, 2019). For example, by wearing AR glasses and looking at the crops, the farmer can obtain vital information, such as whether the crops are infected or when they can be harvested, as exhibited in Fig. 6. Thus, farmers can perform farming in a more productive way that potentially minimizes labor, time consumption, and crop losses and ensures quality yield.

VR can be used for immersive simulated agricultural training and practice (Li, 2008; Wang et al., 2017). For a fair cloud VR experience, a prerendered 4 K 360° video requires a data rate of only 20–60 Mbps and latency less than 50 ms, whereas for an ideal VR experience, a prerendered 12 K 360° video requires a data rate of at least 440 Mbps and a latency less than 10 ms. An interactive VR experience further pushes the limits of the connectivity requirements. For a 6-degree field immersive interactive VR experience with a content resolution of at least 8 k, a high bandwidth of at least 1.5 Gbps, and a latency less than 8 ms is required. 5G solves the high bandwidth demands of VR and AR for cloud streaming. With cloud VR, all the content can be rendered in real time in the cloud, which minimizes the computational load on the VR kit. In addition to immersive prerendered video experience, 5G cloud VR opens the possibility of extremely interactive VR services for agricultural education training and practice.

A comparison of the network connectivity requirements of various VR services is tabulated in Table 3. With a fast and stable mobile

Table 2
Comparison of different protocols in the wireless network.

Technology	Frequency Band	Range	Maximum Data Rate	Channel Bandwidth	Modulation	*Scalability*	*Reliability*	*Low Latency*	*Low Module Cost*	*Low Power*	*Mobility Support*	*SLA Support*
LoRaWAN	915–928 MHz	5 km	50 kbps	100 Hz	BPSK/QPSK	No	No	No	Yes	Yes	No	No
ZigBee	902–928 MHz, 2.4 GHz	Less than 1 km	250 kbps	2 MHz	BPSK/QPSK	No	No	No	Yes	Yes	No	No
Bluetooth	2.402–2.480 GHz	Classic: 100 m BLE: 240 m	Classic: 3 Mbps BLE: 2 Mbps	15 MHz	GFSK/ DQPSK/ DPSK	No	Yes	Yes	Yes	Yes	No	No
Wi-Fi	2.4–60 GHz	100 m	10 Mbps	20 or 40 MHz	BPSK/ QPSK/QAM	Yes	Yes	Yes	Yes	Yes	No	No
LTE-M (Rel13)	1.7–2.1 GHz, 1.9 GHz, 2.5–2.7 GHz	12 km	1 Mbps	1.4 MHz	BPSK/QPSK	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LTE-M (Rel14)	1.7–2.1 GHz, 1.9 GHz, 2.5–2.7 GHz	12 km	4 Mbps	5 MHz	BPSK/QPSK	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NB-IoT	700,800,900 MHz	15 km	200 kbps	200 kHz	BPSK/ QPSK/ 64QAM	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5G NR	Below 6 GHz, 20–60 GHz	200 m	1 Gbps	400 MHz	OFDM/ BPSK/QPSK	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Fig. 6. Illustration of AR using AR glasses.

Table 3
Connectivity requirements of different VR services.

VR	Content		Connectivity	Bandwidth	Latency	Remarks
PC VR	Simulations, Gaming, Education		Wi-Fi			Rendering and motion processed in the CPU/GPU of a PC
Mobile VR	360° video		Wi-Fi & 4G	20 Mbps (4 k)	50 ms	Prerendered video, motion processed in smartphone
Cloud VR	All types of extreme immersive and interactive content	Video	5G	140 Mbps (4 k) 440 Mbps (8 k)	2–10 ms	Real-time rendering and motion processing in the cloud
		Interactive		260 Mbps (4 k) 1 Gbps (8 k)		

network, transmission of user inputs and rendered display and audio output back to the user can be performed at an ultrareliable low latency, thus providing an immersive experience to the users in real time without motion sickness (Sukhmani et al., 2019; Torres Vega et al., 2020; Orlosky et al., 2017). The deployment of 5G will enable online immersive learning using cloud VR and AR over traditional classroom learning by providing realistic and impactful engagements for learners.

5.5. AI-driven robots

The combination of AI with 5G technology produces new developments in live video monitoring, remote diagnostics and on-site prescription to support smart farming, and it is also used to stabilize drones and robots by controlling their parameters accurately. AI in agriculture is projected to grow at a CAGR of 25.5% between 2020 and 2026 (AI in Agriculture Market by Technology, 2020). AI in the field of agriculture is constantly emerging to provide innovative solutions to improve crop yield, packaging, feeding farm animals, etc., and AI-powered robots and autonomous systems are set to transform agricultural industries. In recent years, agricultural robots have been used for planting different varieties of crops autonomously over several acres of land. Robots equipped with computer vision and machine learning technology are used to detect and eliminate weeds precisely over a given region without affecting the crops. Robots are designed to navigate themselves throughout the field using GPS and identify and collect fruits and vegetables that are ready for harvesting (Gonzalez-de-Santos et al., 2017; Skvortsov et al., 2018; Pedersen et al., 2006; Ramin Shamshiri et al., 2018; Emmi et al., 2014; Noguchi and Barawid, 2011; Ball et al., 2017; Defterli et al., 2016). Machine vision technology is often a core competency of these robots, enabling the robots to see, identify, localize, and take some intelligent site-specific action on individual plants. These robots have a laser rangefinder for navigation and a camera for pattern recognition/computer vision. The laser rangefinder is used to detect the obstacles in the path of the robot to avoid collision. AI algorithms can process all the data at a fast rate and instruct them to perform complex tasks, such as inspecting individual plants and fruits using bionic hands to determine their health condition. All the information gathered is stored in a data repository and accessed by other robots to perform some tasks rapidly without human intervention. For example, when a robot finds pests after close inspection of some crops, it flags the locations and details of the pests or diseases present. Robots can be designed to control pesticides, steer autonomously to the flagged position, and spray the necessary pesticide based on the types of pests or diseases. All these sequences of tasks have to be performed over a large area rapidly and are accomplished using high-speed reliable intercommunication among the different deployed robots, such as

- Plowing and seeding robots
- Watering robots
- Harvesting robots
- Spraying/weed-eliminating robots
- Packaging robots
- Animal monitoring bots
- Greenhouse management robots

AI-powered facial recognition is being used to detect the emotional state of pigs and to raise a flag when any abnormalities are detected (Hansen et al., 2018). It is also used to identify individual cows for easy monitoring and tracking of their movements (Dao et al., 2015; Sumi et al., 2017; Jorquera-Chavez et al., 2019; Guzhva, 2018). Some robots can package harvested products for shipments. The different kinds of AI-powered robots are displayed in Fig. 7. The greenhouse is an ideal place for multiple types of robots to flourish, as it is a controlled environment with a closed structure. A large number of robotic arms can be deployed in a greenhouse to perform multiple tasks, such as seeding, spacing, watering, and harvesting, applying the benefits from the large device

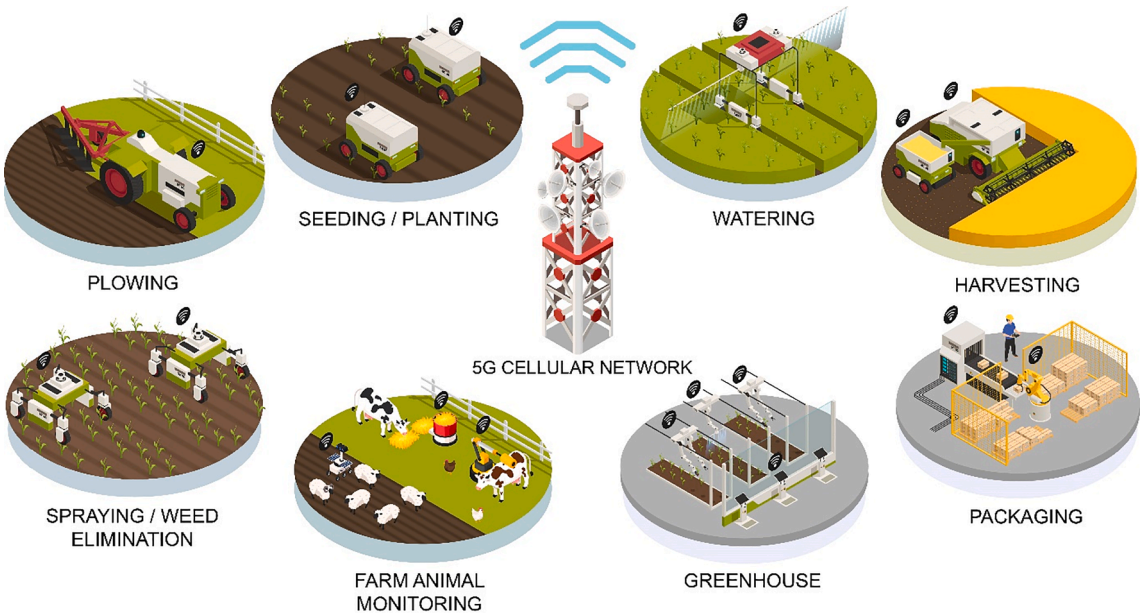

Fig. 7. Illustration of different kinds of AI-powered robots.

capacity of the 5G network.

The robot can navigate its environment and can be controlled from anywhere through cloud computing by the transaction of a large amount of data using 5G. With a 5G mobile network, all these robots can transmit, with superlow latency, real-time images and videos acquired from different attached sensors (Aijaz et al., 2017; Dohler et al., 2017; Voigtlander et al., 2017). Some of the modern autonomous robots demonstrated in Fig. 8 can be controlled simultaneously and remotely using a 5G cellular network.

5.6. Data analytics and cloud repository

Data are one of the most important features of the progress of technologies driving the smart agricultural industry. All the data that are collected from different sources, such as IoT sensors, drones, and robots, on several farms are stored in a cloud data repository. 5G and edge computing will enable the swift transfer of data to the cloud so that real-time analytics and machine-to-machine communication can streamline and automate the farming process. Some important applications of data science are as follows:

- Early detection of diseases
- Weather prediction and coping with climate changes
- Digital soil and crop mapping
- Fertilizer recommendations
- Pesticide recommendations
- Autonomous irrigation system
- Yield prediction and trends
- Generating insights

Image source: Xinhua, www.chinapost.com.cn, www.gsma.com

Fig. 8. 5G-enabled autonomous robots employed in agricultural activities.

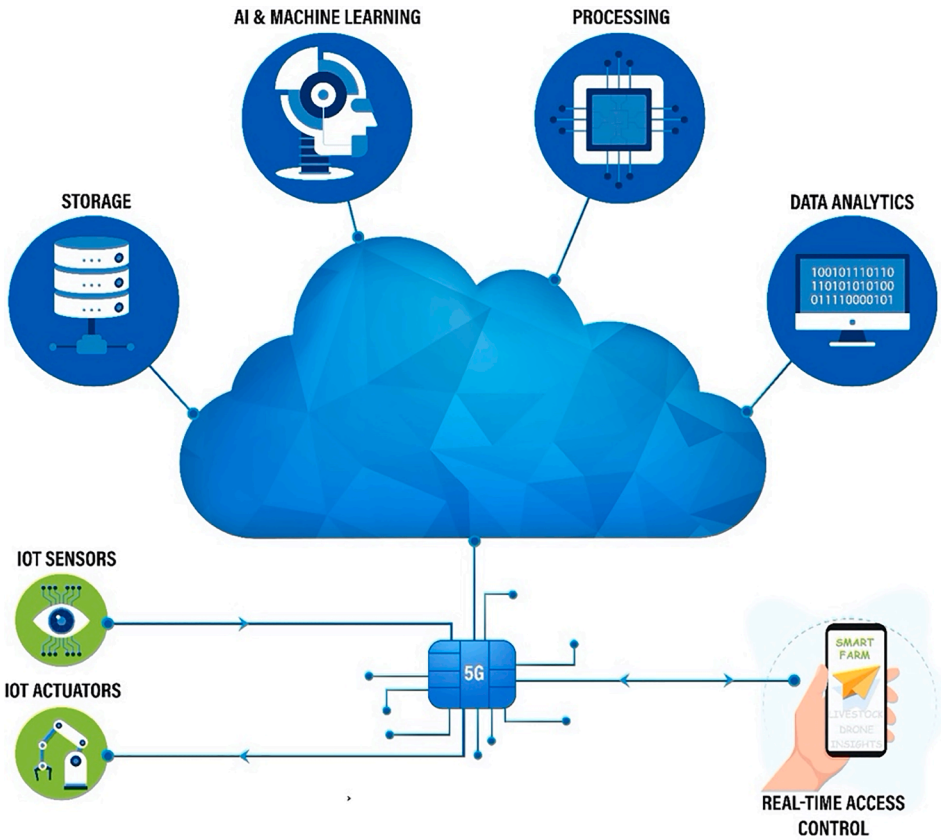

Fig. 9. Cloud data mechanism.

These larger data (varying from megabytes to terabytes) must be transferred from different sources to the cloud, as depicted in Fig. 9, and back to users such as farmers and data scientists. For example, upon close inspection of a crop, a robot captures an image of the crop after suspecting pests, and the robot transfers the image to the cloud for pest detection using computer vision techniques (Bongiovanni and Lowenberg-Deboer, 2004; Gil et al., 2007). Then, the results are returned to the farmer and the actuator robot, which is designed for pest control to take the necessary action, as shown in Fig. 10.

Cloud-based edge computing is predominantly used in smart robots to reduce complexity. The cloud can be used as a data center or host to store the control services of robots for navigation and data processing. For example, captured images from surveying drones manufactured by XAG, Guangzhou, China, are processed in the cloud in real time. These data are analyzed instantly by agriculture intelligence (XAI) to generate AI prescription maps to fulfill the variable-rate application (VRA) of plant protection drones or automated agriculture machines Edge computing removes the need to use the graphics processing unit (GPU) in the robot by placing the GPU in the cloud edge server. As the bandwidth required to process the data is very high (120 Mbps), only 5G can achieve this capability. The physical size, complexity, power consumption and cost of the robots are significantly reduced. All control services for facility management, navigation, and data processing are located in the cloud, running in data centers or on dedicated hosts. 5G will substantially improve the experience of data transfer over existing mobile networks. With a transfer speed of 10–30 Gbps, a large amount of data can be reliably transferred across multiple devices, keeping the data loss to a minimum, i.e., connection downtime will be reduced, and retransfer of data that utilizes the bandwidth unnecessarily can be avoided. Due to its state-of-the-art reduced latency, all these data can be accessed securely in real time. Cloud computing takes full advantage of 5G technology, providing faster data processing at the cloud with minimum round transfer latency between various 5G connected devices and thus enabling maximum productivity of a smart farm (Hassan et al., 2019; Song et al., 2019; Siddavaatam et al., 2019). Fig. 11 demonstrates the overview of 5G network applications in smart farming, comprising sensors, drones, robots, smart devices, cloud computing and data analytics. Similarly, Table 4 explains why 5G is advantageous in agriculture for different tasks.

All these use cases leverage the four most important 5G features: device density, ultralow latency, ultrareliability and security. These different components of smart agriculture, such as drones, IoT sensors, and robots, seamlessly work together to maximize productivity and strongly reduce the cost incurred.

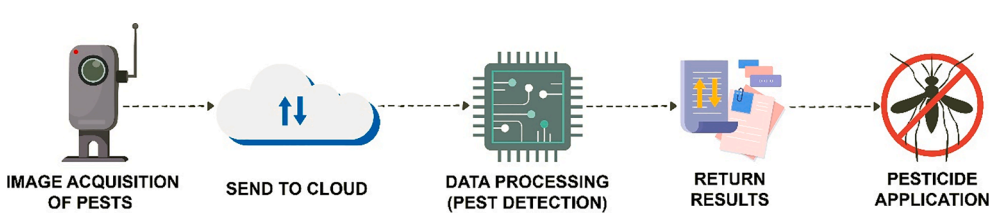

Fig. 10. Synchronous operation of different 5G enabled devices to control pests.

Fig. 11. Overview of 5G application in smart agriculture.

6. Future outlook

Theoretically, 5G is far ahead of any current-generation mobile network. Various telecom operators are performing tests to push metrics to their limits to obtain the maximum performance from their systems. A dense network is crucial for the IoT to provide support in connecting a large number of devices. Telecom operators project several use cases of 5G technology, in which the entertainment industry, health care and agricultural sector are among the top to be highly beneficial. 5G technology has substantial scope in the agricultural sector and can bring the future of farming "connected farms" one step closer to reality. Telecom operators can provide three types of services, namely, connectivity, vertical integration and partnership, in smart farming to enhance productivity. Beyond connectivity services, telecom operators can offer end-to-end solutions in precision farming, which leads to enhanced growth. They can also endorse the deployment of IoT devices at different levels by providing several services, such as provisioning, device configuration, device management, security, billing, location-based services, application facilitation and data analytics.

With 5G technology and cloud computing, the live feed and significant crop data can be streamed to mobile phones. This augments the overall user experience of farm management and food safety. Farmers can remotely perform crop inspections more accurately without the need for physical presence in the field. Additionally, this capability minimizes the gap between the farmer and the consumer by keeping consumers well informed on the availability of produce.

Some noticeable examples of 5G technology being used in the agricultural sector and current happenings that move toward this transformation are as follows.

i. Huawei Technologies announced a partnership with XAG, a manufacturer of agricultural drones, to implement a smart agriculture project to trial the use of 5G, AI and cloud computing in agriculture (XAG, 2019).
ii. A smart greenhouse in Zhejiang Province, East China, started producing tomatoes with the help of 5G technology. Various sensors are deployed to maintain the ideal temperature and humidity, feed plants with nutritive substances and play light music. All these sensors are connected to the 5G network of China Mobile. A separate 5G-enabled pest management system is used in the greenhouse (Roy, 2019).
iii. In 2019, the British Agricultural Technology Research Center developed a 5G-enabled collar that was outfitted to 180 cows to track their movements and eating habits. Dairy cattle at an English farm in Somerset were given collars that interact with a robotic milking system (Reuters, 2019).
iv. The National Institute of Agro-machinery Innovation and Creation (CHIAIC) in Luoyang in the central province of Henan launched a hydrogen-powered 5G smart tractor (model: ET504-H) that can self-drive. With 5G technology, it can monitor the real-time running status of the vehicle as well as the surrounding working environment, which will effectively improve the reliability of the operation (China launches first hydrogen-powered 5G smart tractor- China.org.cn, 2020).
v. In 2019, Sunrise, Huawei and Agroscope, the Swiss Center of Excellence for Agricultural Research, signed an agreement to establish a smart 5G farm (Sunrise and Huawei enter into strategic partnership with Agroscope for 5G farm - Huawei, 2019).
vi. Qualcomm introduced its new RB5 system, which includes software, hardware and tools for advanced robotics and drones with 5G connectivity (Qualcomm Launches World's First 5G and AI-Enabled Robotics Platform | Qualcomm, 2020).
vii. FlytBase, an enterprise drone automation platform, provides a cloud-based drone management solution and stream HD video feed over 5G at ultralow latency (FlytBase Enhances Drone Software with FlytNow Upgrades - DRONELIFE, 2020).
viii. Coretronic Intelligent Robotics Corp (CIRC) demonstrated autonomous drones capable of real-time 4 k video transmission and remote inspection using a 5G network in Taiwan.

7. Conclusion

Currently, technology plays a vital role in all fields, such as building construction, the automobile industry, aerospace, the telecom industry,

Table 4
5G applications in agriculture.

Agricultural Tasks	Why 5G?
Real-time monitoring	Energy efficiency • IoT sensors are needed for a prolonged time with a limited energy source. Device density & data volume • A massive amount of IoT sensors needs to be deployed for precise agricultural practice, which in turn increases the required data exchange by a large amount. Ultralow latency • For the maximum throughput and productivity, lag-free monitoring is required to take necessary action. Reliability • Reduced downtime is sought.
UAVs	High data rate • A large amount of sensory data has to be transferred to the ground station. Ultralow latency • Drones need to make the necessary decision instantly without delay. Reliability • Downtime has to be minimized to avoid uninterrupted service. Energy consumption • For a prolonged airborne sensing time, consumption of energy incurred for transmission must be reduced between other UAVs and the ground station. Security • A security breach would lead to loss of data and hardware.
AR & VR	High data rate • A large bandwidth is required. Low latency • Interactive VR and AR service needs to be instantaneous to avoid motion sickness.
Virtual consultation & predictive maintenance	High data rate • HD streaming service from multiple sources requires a high data rate. Ultralow latency • Real-time data feed from all sensors and machinery have to be pulled in real time to avoid unnecessary maintenance costs. Reliability • Reduced downtime facilitates maintenance and replacement cost reduction.
AI-driven robots	High data rate • HD videos and other information need to be transferred. Low latency • Cloud processing of data and communication between other elements of smart precision agriculture should be instant for better decision making. Reliability • The downtime should be reduced to ensure uninterrupted service. Energy consumption • Retransmission of data must be minimal. Security • A security breach would lead to loss of data and hardware.
Data analytics & repository	High data rate • A very large amount of data has to be transferred. Ultralow latency • Data from the sensors should be processed at the cloud and sent back at a fast rate in real time. Reliability • The downtime should be minimized and the throughput should be maximized. Security • All these data should be securely stored and transferred to avoid a security breach.

and the military field, to develop society. In this regard, ancient fields such as agriculture are also demanding technology (here, smart farming) to produce higher crop yields with less human intervention in a limited period. However, smart farming requires high investment costs, better coverage and connectivity and higher bandwidth to handle the vast amount of data among a large number of sensors and devices deployed remotely. Though the 4G network provides a large bandwidth and sufficient coverage, it is not sufficient to transact the enormous amount of real-time data between the substantial number of devices. The advent of 5G satisfies current requirements and demands in smart farming to enhance productivity with minimal human labor. In the future, all countries will introduce 5G networks in all fields; hence, internet costs will be reduced considerably, and connectivity will be enhanced. The investment costs for smart farming will be reduced significantly because of 5G usage, which is a boon for farmers. Farmers will be well equipped for smart farming, with the ability to predict and prevent crop disease using their mobile phones. Mobile operators will make significant contributions to smart agriculture by extending their physical infrastructure. Sensors will collect the data from the field to be stored in the cloud and analyzed whenever convenient. Sophisticated sensors with a long-life battery will become smaller and cheaper, and networks will become more intelligent and secure. Automated driving systems, AI, deep learning and cloud-based mobile applications will help farmers increase their yields by many times. Future farms termed "connected farms" will be based on connecting, collecting and analyzing large amounts of data to enhance productivity by maximizing efficiency. Although 5G can provide numerous use cases and advantages to the agricultural sector, it will substantially change the nature of jobs. The possibility of the number of agricultural jobs shrinking is high. 5G has not yet been fully explored, new applications and technologies will be defined in the future, and the full effect of 5G will be determined over time.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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