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Transforming Agriculture through Digital Technologies: Unlocking the Potentials of Disruptive Technologies

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Abstract: Farmers require timely access to information on emerging varieties, climate trends, optimal production methods, and advanced agronomic practices to enhance productivity. Digital technologies, including the Internet of Things (IoT), drones, and Artificial Intelligence (AI), bridge geographical gaps, connecting African farmers to global best practices. Through digital platforms, farmers gain valuable insights, adopt improved techniques, and boost crop yields. This paper explores the transformative potential of digital technologies in African agriculture, fostering informed decision-making, increased efficiency, and sustainable food security.

***Index Terms*: Digital Technologies, Disruptive Technologies, Internet of Things (IoT), Data Management, Drones, Crops Monitoring.**

I. INTRODUCTION

A significant portion of the gross domestic product (GDP) of developing nations comes from the agriculture sector [1]. Due to the ever-increasing population, this business may not be able to keep up with the needs of growing technologies and the population growth. Even now, the world population is over 8 billion, even before the 2030 and will reach over 10 billion people by 2050. With more than 1.4 billion people apiece, China and India are the two most populous nations in the world by population, making up 19% and 18% of the entire world's population, respectively. China surpassed India in population in 2022. In order to provide a consistent supply of jobs for their expanding populations, agriculture is essential to the economies of both nations. The Internet of Things (IoT) [101] is a contemporary mechanism for development that has assumed control over networked cloud applications, including mechanical, electrical, and digital devices as well as people with unique identities (IDs). The ability to send data without a human transmission interface is by far the most crucial aspect of the IoT. The use of Wireless Sensor Nodes (WSN) is the greatest solution to the issue since the field is extended across a sizable area of farmland for agricultural or animal viewing. Although they are not as numerous as the sensor nodes, the actuator modules are connected to the Personal Area Network (PAN) since they use a significant amount of electricity. Using current Local Area Network (LAN) and Internet infrastructure, this comprehensive framework may be incorporated into an IoT-based system. Most emerging nations are progressing with agricultural digitization. Crop breeding, insect management, agricultural management, and the creation of meteorological data are all prevalent practices in Japan. Large data cloud systems, government databases for agriculture, research institutions, and libraries are all accessible to farmers in the United States (US). The database can be used by farmers to learn about the most recent market prices, crop enhancement techniques, and advancements in agricultural technology. In order to create farms with the highest yields and benefits, farmers can utilize computers to help them choose the best crops to sow, the best seasons to grow them in, and the best farming method to employ. Numerous agricultural management specialties are covered by plug-in or analogous solutions from well-known financial management information system (FMIS) suppliers as Wisu and Agrineuvos. For agricultural production education, it is crucial to acknowledge relevant and available information. Agricultural information serves as the cornerstone of an agriculture management information system (AMIS). The accuracy with which agricultural data is gathered and processed has a significant impact on how it is managed. Data collection frequently involves considerable costs and technology since the farming ecosystem is a rather complex ecological framework with many variables spanning from the environment to the human, from ecology to economics, and from geography to culture. The use of IoT in the agricultural sector may improve sensing and monitoring of production, including farm resource use, animal behavior, crop development, and food processing [93, 95]. This study has made a significant contribution in this regard. Additionally, it aids farmers in understanding certain agricultural circumstances, such as how the atmosphere and climate influence the development of weeds, pests, and diseases, among other things [96, 102]. In [107], Artificial Intelligence (AI) in Agricultural

Farming Systems: Benefits and Challenges is covered. In [106], the benefits and challenges of information systems for agricultural management are discussed.

II. MANAGEMENT OF DATA IN AGRICULTURE

The most current paradigm based on agricultural data to develop is smart agriculture, which is often referred to as automated farming. It was made possible by developments in data processing and telecommunications, which were integrated with the precision agriculture idea that already existed to increase operational accuracy. This is how smart agriculture works. Farmers use technology to collect data from agricultural fields, which is then evaluated to come to appropriate management and operational conclusions. Farmers used to have to travel to the ground farm in person to check on the condition of the plots and to examine decisions that were made without their knowledge. This approach is ineffective for a number of reasons, including the fact that many industries are too vast to be properly addressed within the confines of legal norms. Innovative management techniques are making practical contributions to smart agriculture. Additionally, even if some farmers have accumulated extensive knowledge via a range of experiences, technology can offer an automatic technique to find unforeseen problems that are challenging to notice with routine eyesight assessments. Younger farmers are more likely than older farmers to utilize new agricultural technologies because they will use smart tools or devices to supplement their limited knowledge. However, in recent decades, the average age of farmers has increased significantly: it is now 63 in Japan, 60 in Africa, and 58 in the US and Europe [2]. Thankfully, a number of policies are being updated and expanded throughout Europe to support generational transformation by expanding access to start-up financing, loans, market advice, and coaching. Regeneration of generations involves more than just lowering the retirement age for farmers in rural areas. It also entails motivating the most intelligent and engaged young farmers to use technology to further successful agribusiness methods. Young farmers must adapt their current practices in order to achieve sustainable food security and competitiveness in the food chain.

2.1. Data Gathering using an Internet of Things (IoT)

IoT and agriculture have always been associated with the use of sensors and other instruments to transform any aspect of farming operations into data. It is projected that more than 10% of US farmers will utilize IoT devices on their plantations, which total more than 2400 million acres. The core of "agricultural 4.0" is the Internet of Things. Because it makes it possible to generate such a large amount of useful knowledge, IoT technology has in fact become a catalyst in the agriculture industry. Improvements in these technical breakthroughs are anticipated to have a substantial impact on the farming industry. It is anticipated that the IoT would be able to increase agricultural output by over 70% with current methods by 2050. This is a good development since, according to Myklevy et al., the world's food supply must increase by 60% by 2050 to support the world's expanding population of about 900 million people. Better harvests and reduced prices are the key advantages of IoT systems. A typical farming operation that employs IoT can reduce energy use by up to 8% while increasing yield by up to 2%.

2.2. Massive Data Analysis

Due to the vast quantities of data streams available for farm management, a new type of automation technique is needed to produce organizational big data. However, it is unlikely that the quantities of data retrieved from the vast majority of industrial or agricultural topic areas will match the requirements for classification as big data. Regarding big data, it may be divided into three categories: quantity, speed, and variety of organisms. Authenticity and valuation lead to the following:

(a) Volume: Databases that are too big to be recorded, preserved, handled, and analyzed using traditional techniques are linked to volume. Based on generally accessible computer resources and typical dataset sizes, which frequently start in the terabyte region, it provides an estimate of the size of a database needed to be termed enormous, which varies by respected field.

(b) Velocity: The ability to learn, absorb, and experience events as they happen is referred to as "velocity." These systems function in real-time when it comes to agriculture, among other things by extracting local information to implement various chemical dosages in machinery with variable-rate delivery mechanisms.

(c) Variety: The word "variety" alludes to the several informational mediums (text, audio, and video), as well as the varied levels of complexity. Images and data from soil or temperature sensors are just two examples of the types of information used in agriculture to deal with dynamic conditions.

(d) Veracity: The word "veracity" refers to the information's consistency, dependability, and validity.

(e) Valorization: When one wishes to impart awareness, respect, and inventiveness to others, it is known as valorization. Big data is only useful for managing agriculture under specific conditions, depending on the plantation and the rate of technological adoption. 34 surveys [3] discussed the use of information systems in farming, while Wolfert et al. [4] did study on the application of big data in contemporary agriculture. The Agriculture Big Data Platform, which was introduced by the Organization of Global Agricultural Research Centers (OGARC) in order to stay up, claims to answer concerns about agricultural expansion more quickly, more economically, and more successfully than the current methods.

2.3. Robotics and Artificial Intelligence (AI) in Agriculture: Helping Humanity

Large technical issues are frequently solved by transformational technology, and Agriculture 5.0 is unquestionably one for the first half of the twenty-first century. Farmlands that use Precision Agriculture standards and technology, such as autonomous operational processes and automated decision support systems, are referred to as having Agriculture 5.0. Agriculture 5.0 actually incorporates many robotic and AI technologies. To work the fields and increase profitability, farms have traditionally resorted to a significant amount of seasonal labor. However, the culture has evolved from one where many people lived in fields as part of an agrarian society to one where more people live in towns, which has resulted in a scarcity of employees on farms. A Forbes article claims that agricultural robots assist humans by more quickly and effectively harvesting crops. While agriculture is currently developing technology solutions to help farmers with monotonous activities, moving agricultural systems into the modern paradigm of Agriculture 5.0, robots are still incredibly slow compared to people in so many aspects. According to Reddy et al. [5], agricultural robots has improved productivity and lowered farm running costs in several countries. However, as with previous innovations, significant obstacles must be overcome in the first phases. For the majority of farmers, especially those with small farms, these technologies continue to be exorbitantly expensive due to scale economics, which makes small individual farms less lucrative. Agricultural robotics will undoubtedly be used in the future as a way to boost production as technology becomes more accessible. In 2015, farming and agriculture production decreased globally. These issues and the growing demand for higher returns led to the creation of agricultural robots. A Verified Market Intelligence report found that agricultural robots may carry out field tasks more effectively than farmers, which would boost the global agriculture and crop production market. Within the previous five years, agriculture technology firms have raised more than $800 million. Startups that employ automation and machine learning to address issues in agriculture have grown in 2014. This was at the same time as interest in artificial intelligence significantly increased (AI). Venture financing for AI has significantly increased during the past five years [6, 7]. By 2050, the Food and Agriculture Organization of the United Nations (FAO) predicts that there will be more than 9 billion people living on Earth. This innovative approach to agriculture offers the possibility of getting more done for less money. High-tech sensing technology will aid in the problem-solving process in agriculture. These technologies will provide accurate information on the environment, crops, and soil, allowing for the practical implementation of phytosanitary products that will significantly minimize the use of herbicides.

III. IOT-BASED AGRICULTURE ANALYSIS OF THE CURRENT MARKET

Some of the most frequently utilized IoT solutions in modern agriculture are pesticide or fertilizer management, plant health, disease prevention, irrigated agricultural monitoring, soil conservation, distribution network traceability, automobile, and machine and equipment control. The IoT system for smart farming with the highest adoption rate is agricultural crop monitoring. These solutions have also been developed for use in a variety of agricultural settings, including greenhouses, orchards, and arable fields, among others. Farmers depend on crop surveillance, which is why this kind of equipment is so common in agriculture. In order to collect environmental data from plantations, such as temperature, humidity, brightness, and other factors, IoT systems for crop monitoring were developed. This information can be used by farmers to get a more complete picture of their plantations. The strength of pricing [8, 9], alfalfa [10], and maize [11] crops, as well as greenhouse environmental conditions [12, 13, 14], have all been evaluated using comparable data. A number of agricultural applications have led to the development of automated irrigation systems. Many IoT systems are designed to employ sensors to detect soil moisture and monitor irrigation sources in order to improve agricultural water use. As an alternative, you can determine how much water is available when watering the crops by combining meteorological and humidity data [36]. To identify and prevent infections on plantations, IoT disease control strategies are used. For this reason, these IoT systems collected various environmental and plantation data, such as plant images [33], sounds, temperature, humidity, and more. There are several approaches used to analyze this data. AI and image processing are two examples. For instance, [51] is experiencing innovation due to the Internet of Things. It examines photographs of a sugarcane plant and finds pesticide contamination on the plant's green leaves. In contrast, [52] developed a gadget that can record sounds made by larvae inside of trees that is Internet of Things enabled. IoT chemical control systems let crops apply fertilizer and pesticides more efficiently. Consequently, these technological solutions collect data from crops (such as nitrogen, salinity, or PH). These Internet of Things (IoT) devices can identify crop zones that may require the administration of fertilizer or pesticides. For instance, aerial images of crops can be used to assess the nitrogen level in a sizable plantation [53]. The exact field that requires fertilizer may be found using these images. A self-sufficient robot that improves pesticide distribution in greenhouse growing regions was also developed by [30]. The platforms for industrial IoT soil science aim to characterize various soil properties that could be used for planting. Examples of applications for these systems include identifying soil nutrients [56], calculating soil water content [54], analyzing water consumption patterns [55], and using them as a weather station with air quality measurement [57]. The primary goal of the Internet of Things (IoT) technology for car and machinery management is to gather and analyze data from agricultural plants and facilities, including trucks, harvesters, and tractors. IoT solutions must therefore handle certain characteristics of agricultural equipment, like mobility. In order to maximize their maintenance interval, sensors take inputs from the machinery itself, such as the condition of the implement, engine performance, or rpm. Additionally, opportunistic computing has been employed to collect data from distant crop fields using tractors fitted with sensors as agricultural equipment has grown more mobile [62, 63]. The environment's impact on sensor information interchange can be brought on by sensor node distance [59], a breakdown in communication in farmlands [63], or even the impact of vegetation on signal transmission. Each agricultural scenario also provides specific obstacles for productivity. Additionally, both are impacted by meteorological factors as snow, fog, and sun irradiation. Electronic sensors were utilized to cover these scenarios in almost 96% of the studies assessed. The fact that these sensor nodes are approved, reasonably priced, and readily accessible, as well as meeting the crucial monitoring condition for IoT technology for smart agriculture, validates this descriptive approach. These sensors are used to collect data in real-time on a range of agricultural parameters, such as meteorological variables, substrate characteristics, brightness, CO_2 concentration, and images. Additionally, a small percentage of papers (4%) concentrated on the design of specialized sensors for monitoring particular agricultural factors, including nitrate [56] and plant leaf evaporation to compute hydric pressure in tobacco crops [65]. In order to gather information about farming from a variety of sources, including as the environment, agricultural productivity, and substrates, a wide range of sensors were integrated in IoT systems for modern farming. In IoT solutions, electronic detectors are used to gather parameters. For instance, temperature, luminosity, and humidity [14, 23, 58]. In addition, electronic sensor nodes were set up to collect data from the soil surface, such as moisture, temperature, and nitrogen, for substrate management. Similar to this, pH sensors are frequently used in hydroponic farming techniques to measure the water's alkalinity or acidity. Crops were photographed using multispectral sensor systems and cameras in order to be tracked. Robots are being used to take incredibly precise pictures of plant leaves, or the unmanned aerial vehicle (UAV) [103] may be used in a number of different ways to capture aerial pictures of vast plantations [8, 9, 11]. The equipment selection plays a crucial role in the creation of an IoT application because it influences both costs and available technology. 60 percent of the papers looked at the tools used to support IoT applications. Additionally, SBCs were discussed in 40% of the studies analyzed. SBC use is justified by its affordability and scalability [21], which allow for the creation of individualized IoT systems. Some SBCs, like Arduino, come with an integrated development environment (IDE). It enables the development of specialized software that may be used to run as software on the microcontroller. Additionally, the Raspberry Pi is compatible with a wide range of operating systems, including Raspbian, Mozilla Web Things, and Ubuntu Core. Several of these operating systems' source codes can be changed. These operating characteristics also make it possible to run programs created in Python and other programming languages [74]. Moreover, by adding extra components like transceivers or sensing devices, the capabilities of SBCs can be improved. SBCs can function as gateways or core networks in IoT strategies thanks to this functionality. In 82 percent of the publications that discussed SBCs, the use of ESP boards (including ESP12, ESP32, and ESP8266), Arduino, and Raspberry Pi was addressed. Arduino is a well-liked option for experts and hobbyists alike since it is an open-access platform that can be used to build a range of gadgets. Intelligent sensor systems are becoming more important in IoT applications for crop monitoring. Rain sensors, sun radiation detectors, and soil humidity sensors are coupled as sensor nodes. The health of a vineyard is then assessed using the microcontroller board. Similar to [75], a Raspberry Pi is used to gauge the temperature inside a greenhouse. Through IoT devices serving as gateways, long-distance communication protocols can be used to quickly link WSNs to the internet. Through a gateway, a WSN employing three separate protocols (Wi-Fi, ZigBee, and Bluetooth) was connected to a remote server using 3G. Data is obtained from the sensors through LoRa and retransmitted via 4G to a cloud-hosted platform by the Lora WAN gateway developed in [49]. Through the use of cellular network technologies like 3G and 4G, users may connect over great distances and send large amounts of data quickly. UAVs are valued for their capacity to quickly and affordably monitor large crops. UAV systems with multispectral sensing equipment and cameras are used for this specific purpose to take flying pictures of vast fields of crops. These images are used by the IoT solution to measure agricultural parameters like the leaf area index (LAI). A statistic used to determine how much vegetation is present in a specific area is called the LAI. LAI can be used in conjunction with other indicators to measure and ascertain the quantity of nitrogen in rice production [9], calculate the vigor of rice and maize crops [8, 11], and ascertain the existence of pests in sugarcane crops [51]. Additionally, [67] optimizes pesticide and fertilizer applications in agricultural output by using UAV systems. The transfer of acquired data to an endpoint, such as an IoT-based database or webserver, frequently occurs outside of a wired or wireless network. In 60% of the articles we studied, the set of network rules used in the IoT strategy were discussed. The two most frequently used communication protocols for wired networks were Ethernet and CAN. The Lora WAN and wireless network configurations are by far the most popular for long-distance wireless connectivity. For instance, 3G, GPRS, and so forth. Similarly, the most popular short- to medium-range wireless channel technologies are Bluetooth, ZigBee, and Wi-Fi. In some agricultural applications, a variety of network protocols are used to facilitate connectivity between smart equipment like routers and motes (e.g., greenhouse, orchard, arable land). The creation of both short-range and long-range networks is possible thanks to this group of data structures. The IoT implementations that were evaluated used a variety of hardware for middle-range and short-range networking, including Wi-Fi, ZigBee, and Bluetooth. Despite the fact that Wi-Fi is a ubiquitous infrastructure that is very easy to establish, this general need for it may be highlighted. Despite this, because to Wi-Fi's energy requirement, energy-efficient technical advancements like Bluetooth and ZigBee continue to be widely used. For instance, the ZigBee protocol was used to send data from a farm to an inaccessible server and to set up a Bluetooth-enabled node to monitor data that was sent directly from a field to a smart device. Long-distance networks like cellular networks, Sigfox, and Lora WAN were employed in the examined publications on IoT deployments. Cellular network-based smart agricultural technologies are increasingly popular. This claim may be supported by cellular networks, which allow IoT devices to connect across great distances and at higher speeds. A watering system is run while data from humidity sensing devices is transmitted over a cellular network to an IoT platform. On the other side, technologies like Sigfox and Lora WAN allow for the energy-efficient transfer of data over incredibly vast distances. Based on these traits, Lora WAN and Sigfox have been used for long-distance connections, providing another option to wireless networks or in locations where cell service coverage is patchy or nonexistent. A Sigfox-based plantation irrigation management system is presented in [36] as a network protocol for the Internet of Things. Additionally, in [34], data is sent to a cloud-based service via Lora WAN from several sensors positioned around the greenhouse. As shown by [62], who examined the effects of 2.4 GHz and 433 MHz signal transmission in expansive estates and an orchard, vegetation itself may act as an obstruction to sensor contact in addition to the distance between sensor devices, gateways, and other network equipment. The abundance of detectors, which could cause wireless signal interruption owing to their close proximity, is another disadvantage of greenhouses [59]. Two examples of wired connections that can be used to solve this problem are Ethernet [78] and CAN [76]. Since this farming method lends itself well to exhibiting entry locations, these systems are being used more frequently in plants. Another crucial factor to take into account when putting an IoT strategy into practice is the topology of a network. [90] states that there are three different types of sensor networks: star, mesh, and tree (also known as a cluster). The number of nodes in the WSN and the distance between the sensor devices and the destination are both impacted by the network's topology [91]. Networks of stars, for instance, consist of a center unit and numerous end nodes. Data is transmitted from peripheral nodes to the central node in this arrangement [59]. The distance between the peripheral nodes and the main node is in this case constrained by the physical layer communication standard. Mesh networks, in contrast, include routing functionality built into each node, enabling multi-hop communication to increase network coverage. Depending on the task description and IoT strategy specifications, 61% of the publications under examination employed the same topology. We employ the LoRa protocol to link sensors to a central location using star topology [36]. Through this hub, which acts as a conduit for cloud-based software, irrigation systems can be monitored via Sigfox. The star topology is also used to wirelessly integrate a variety of sensors inside a conservatory [104]. [59] utilized this topology to keep track of a greenhouse. Cluster networks, also known as tree networks, are constructed from numerous star networks that connect to one another. Both [90] and [50] employed cluster networks to control crops. Data is collected and sent by sensor nodes in [90] from a harvesting station to a router point. Retransmitting messages to the network's main router node, this router serves as a network interface. To increase the energy consumption of sensor nodes, several router nodes are deployed all around the crop. Mobius, Thing Speak, Google, Azure IoT, Thinger.io, and AWS IoT are the cloud computing services that appear the most frequently in the papers that were checked for this study. Because of its open-source design and low technological prerequisites, Thing Speak has emerged as the most often utilized cloud-based framework in all surveyed papers [36]. Only a few of the cloud-based platform providers offer an identical set of features and functionalities, but they all support modeling [68], processing, and farm-level action management in addition to general information management [10, 13, 33, 79]. Furthermore, a number of the publications under review construct private cloud-based systems for the IoT solution, despite the fact that other cloud-based frameworks already exist. Cloud-based solutions provide connectivity for Internet of Things (IoT) initiatives by utilizing cloud computing for data processing as well as storage. Some IoT solutions, such as Thinger.io [25], are entirely dependent on infrastructure providers like Amazon AWS and Microsoft Azure. These services frequently include data processing components with visuals and panels that collect data, or they construct customized pieces using the accumulation of various data sets over time. The huge amounts of data generated by the detectors are processed in database systems to create big data, where an unstructured stream of data is used to acquire crop specifics, thanks to the scalability given by these channels. Because there is so much information, technology is required to reduce reaction time. Big data applications are provided by a parallel computer system known as Hadoop; it has been demonstrated that this technology is more effective in analyzing the benchmark rainfall data from several meteorological stations.

IoT solutions employ a variety of technology and data analysis methods [92]. The three most popular data processing technologies are artificial intelligence, deep learning, and big data. These technologies have the capacity to process large amounts of data quickly. IoT technology is also the most widely used technology for crop monitoring when data processing technology is used. Crop control is also the application mode that needs the most diverse set of data processing technologies. This makes sense given that the majority of IoT solutions for crop monitoring collect a lot of data and use big data analytics and deep learning to interpret it. Big data has been used in several IoT technologies, including soil management and fertilizer control systems. The Prediction of Worldwide Energy Resources (POWER) of NASA, for instance, includes datasets like the market trading price of crops, feedback from users to optimize the irrigation performance, and aids farmers at the stage of material acquisition such as seed and fertilizer. For instance, the data on soil moisture was collected by using sensors and was connected to cloud datasets [55, 87] such as POWER. On the basis of the intelligent foundation created and information gathered from sensing equipment like temperature and moisture monitors in the soil, big data is also used in [27] to monitor irrigation systems and give irrigation advise to farmers. For IoT-based automated management, a number of factors must also be modified. To begin with, simple soil moisture monitoring can be used to control irrigation or cooling systems, as described by [72]. The upkeep of a greenhouse, though, might be harder. According to [14], humidity and temperature in greenhouses are closely related, and changing one would have a cascading effect on the others. IoT solutions use computer vision to process images for purposes like disease and pest identification. According to the reviewed study, computer vision may also be used to manage and clarify the items in a camera-acquired image, such as [31, 51, 80] employing computer vision to detect pests and diseases and using it to identify the different types of fruit in an orchard. Similar to [98], [31] employed the same technology to examine diseases that may lead to morphological deformation on crops. Both studies used computer vision as a monitoring tool to find disease in olive groves. Additionally, crop management systems use computer vision to identify and remove weeds from farms by adding a camera and other physical sensors to a robot to enable it to take pictures of the surrounding vegetation and, using image processing, identify and remove weeds from the scene. robot using computer vision to make sense of the crops and communicate with the farm as needed.

IV. Some of the roles of Information technology in THE AGRICULTURAL sector

1. Improved productivity

To produce, farmers require knowledge of the newest varieties, evolving weather patterns, crop production methods, and enhanced agronomic procedures. Regardless matter where in the agro-ecological zone the farmers are, information technology is essential to guaranteeing they have access to this data. Farmers in Africa can read what farmers around the world are doing because to information technology. By using the knowledge, they have acquired, farmers are able to enhance their farming techniques, which in turn leads to increased yields.

2. Community involvement

Applications for IT enable a number of initiatives, and they can also boost community engagement in agriculture. A community can enhance its output of locally produced commodities by implementing contemporary agricultural techniques. Some areas have a high population density that is mostly dependent on agriculture, and with the use of IT, local farmers' unions may be strengthened, which may boost communal production and raise incomes for all parties.

3. Good post-Harvest practices and Value addition of farm produce.

After practicing effective crop husbandry, the majority of farmers harvest their crops with large yields. But after a few months, they suffered losses as a result of inadequate storage. However, in certain regions of the world, particularly in wealthy nations with adequate storage infrastructure, this is not the case. Thanks to information technology, farmers may now view and learn about the most recent post-harvest handling and storage methods utilized in other nations. By doing so, they can apply these strategies to their own farming practices and minimize crop losses.

4. Improved decision making by the farmer

Information technology makes it simpler to keep track of regular farm activities and create farm records. This will help the farmer choose the right kinds of fertilizers to use, what kinds of seeds to sow, when to sell his or her produce, and how to apply the most effective farming methods.

5. Improved efficiency and service delivery at the farm.

Compared to manual methods, information technology makes it considerably easier to create and maintain farm data, including data about crops, animals, and other resources. Automated farm equipment has also been equipped with information technology. These devices are programmed to perform tasks like spraying or watering even when the farmer is not there, greatly improving the efficiency of service delivery.

6. Weather forecasting and climate smart farming.

Weather and climate are important factors in farming. Farmers can plan when to plant, when to irrigate, and how much water to use for irrigation by using weather forecasts that they can obtain from IT infrastructure. This is essential to the productivity of agriculture.

7. Remote sensing and GPS location.

This is crucial for farming. A farm's location is crucial since it determines the kinds of seeds to be used, how much irrigation to utilize, and most importantly, what kind of crop to plant. Even when a farm is far away, it is simpler to find it with the aid of information technology. This is made feasible by the application of information technology, specifically the global positioning system (GPS), which has allowed agricultural experts to categorize various regions into distinct agro-ecological zones [108].

V. CONSUMER MISUSE OF INFORMATION IN AGRICULTURAL ECONOMIC MANAGEMENT

(1) Lack of technical and professional personnel: Since information technology was used in agriculture only gradually and relatively late in the field, there is a shortage of skilled information technology personnel in agricultural economic management. Furthermore, the information networks of some rural public utilities were not constructed flawlessly, which hindered the development of rural economic management and prohibited farmers from receiving pertinent information on time.

(2) Lack of an appropriate platform Most municipal government organizations are not very knowledgeable about modernizing agriculture. In the context of the information era, government agencies must provide major support for the agriculture industry's expansion. Only after the government conducts an extensive evaluation of the agricultural market, is it able to efficiently guide the growing agricultural industry?

(3) Farmers are not very aware of information. Some relatively backward locations don't have enough depth in agricultural management concepts, agricultural economic growth, and information management for local farmers to be effectively directed in construction. This problem has had a significant negative impact on both the development of the agricultural sector and information management [105].

VI. CONCLUSION

In order to give farmers more control over their fields and teams, precision agriculture employs data sensors, networked devices, remote control tools, and other contemporary technologies [97]. The use of precision agriculture is growing [98]. An extensive overview of the most recent Internet of Things (IoT) applications in agriculture is given in this article [102]. This study showed that whereas simple data processing and decision-making dominated agriculture work a few years ago, the move toward systematic management systems, such as big data and cloud technology, which are used to analyze vast volumes of data, has recently gained attraction. Aiming to enhance farm management, artificial intelligence and computer vision have also emerged as new concepts in agriculture. According to the many efforts described in this article, the bulk of IoT smart farming technologies were utilized to track crop data. The performance of many applications mentioned in this article's discussion is enhanced by the concurrent use of various network protocols [102]. This article also contrasted several communication networks types, using wired network systems for indoor farming (like greenhouses) and wireless network systems for outdoor farming like plantations and arable fields. The analysis in this report showed that IoT applications for smart farming are becoming increasingly unimportant. A farmer will receive a thorough assessment of every facet of his or her business, including crop and animal management, weather patterns, soil quality, and employee performance [93, 99, 100]. By preserving all of this information in one location and making it easily available, the site's history and evolution will be demonstrated uniformly [94]. This article could be used as a resource for upcoming work on IoT system equipment selection and project cost estimation. By accurately predicting the yield levels that will be harvested in each field, it is feasible to create better distribution plans and outline potential income streams [95, 96]. Thus, it can be said that information technology is essential to farming and should be extensively adopted. We must abandon the regional and customary farming practices. Higher yields may be possible with IT-integrated farming than with our familiar traditional farming methods.

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