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PIONEERING AGRICULTURAL TRANSFORMATION: UNLEASHING THE POWER OF IOT AND AI FOR SMART FARMING AND SUSTAINABLE HARVESTS

Shilpi Sindhu*, Bharat Garg, ShikhaYashveer, Anita Verma and Reena Rani
Department of Molecular Biology and Biotechnology, College of Biotechnology, C.C.S. H.A.U., Hisar -125004, Haryana, India
*Corresponding author E-mail: shilpisindhu@gmail.com

ABSTRACT

Agriculture is essential to the advancement of human civilization. Agriculture provides a living for the majority of people in developing and poor countries. Farmers have numerous obstacles in agriculture, such as obtaining expert guidance, monitoring crops, and using manual ways to do vital farming chores such as irrigation, among others. Agriculture-related problems have consistently slowed down the nation's progress. Intelligent agriculture is the only approach that can solve this issue. Utilising the natural resources in a variety of environments is essential for achieving higher yields through Smart Agriculture (SA). Agriculture automation and intelligence are addressed by Smart Agriculture. The automation of picture analysis using computer vision and deep learning models, the Internet of Things (IoT), and associated technologies will be one potential answer to the aforementioned challenges with agriculture and food demand. SA makes use of specialised sensors and algorithms to make sure that crops receive the exact nutrients they require for maximum yield and sustainability. SA entails gathering precise sensors datafrom fields regarding the condition of soil, plants, crops, and climate. From manned or unmanned satellites or airborne platforms, high-resolution photographs of crops are acquired, which are then processed to extract data for upcoming decisions.

Keywords: Smart Agriculture, Agriculture automation, Internet of Things (IoT), Artifical Intelligence (AI)

Introduction

Agriculture holds a pivotal role within society, serving as the primary source for a substantial portion of the global food supply and raw materials for construction. Its significance extends beyond mere sustenance, playing a fundamental role in the economic advancement of nations while offering a plethora of employment opportunities. Yet, despite its critical importance, many farmers persist with outdated and inefficient farming methods, resulting in subpar yields of essential food crops and fruits. Notably, advancements in automation have led to increased productivity, with automated machinery replacing manual labour in several agricultural processes. Hence, to maximize output and meet the demands of a growing population, it becomes imperative to embrace cutting-edge research and technology in farming practices.

The emergence of "Smart Agriculture" represents a concerted effort to address the challenges posed by a burgeoning population and stagnant food production. This paradigm shift in agricultural production integrates the latest technological advancements with traditional farming practices. Leveraging technologies such as the Internet of Things (IoT), big data, cloud computing, and Artificial Intelligence (AI), Smart Agriculture aims to revolutionize various aspects of agricultural operations. These technologies, showcased in Table 1, enable enhanced information gathering, analytical decision-making, precise control mechanisms, efficient resource allocation, and personalized services tailored to individual farming needs.

Driven by the relentless march of Science and Technology (S&T), the agricultural revolution is propelled forward by an emphasis on improving agricultural efficiency and overcoming contemporary challenges. As highlighted by Liu *et al*. (2020), the progress of S&T serves as a catalyst for innovation within the agricultural sector. Through the adoption of Smart Agriculture practices, farmers can optimize resource utilization, minimize environmental impact, and increase overall productivity, thereby ensuring sustainable agricultural practices for future generation sensors installed on agricultural farms may access the exact topography, weather predictions, temperature, and soil acidity. The information gathered by agricultural drones, satellites, and sensors is used in smart farming to assist farmers in planning their work. The robots are capable of doing a variety of autonomous agricultural operations, including sowing, harvesting, and in some situations, post-harvesting. A robot harvester's core functionality should include the following features: detection of the fruit or maladies, collecting the produce without destroying it, guidance of the harvester through the field, navigation in any lighting or climate condition, low cost, and a simple engineering layout (Silwal *et al.,* 2017). Agricultural robots carry out their agricultural tasks either as autonomous self-propelled machinery or as systematically controlled sophisticated devices. Unmanned aerial vehicles (UAVs) or unmanned ground vehicles (UGVs) that are controlled by GPS and GNSS are examples of autonomous vehicles. Lighting and crop changes present difficulties for agriculture automation used to carry out farm tasks (Payne *et al.,* 2013). With a variety of sensors and cameras, modern machine vision algorithms and machine learning models can address these shortcomings. Remote monitoring devices are currently being used to provide useful information to agriculturalists. Wireless technologies are essential for data collection and communication processes. This paper will look at the most recent developments in remote sensor networks and IoT agriculture applications, as well as the problems and challenges faced by network and software for smart agriculture.

Smart Agricultural Wireless Technologies

The most noteworthy technologies that are transforming agriculture today and will shape it in the future include:

IoT in agriculture: IoT is critical to the management of agricultural resources and the monitoring of crop health in the agricultural sector. IoT in agriculture makes use of internet-connected sensors, drones, and robotic devices that perform activities automatically or partially autonomously in order to boost cultivation and reliability. Agribots, also known as agriculture automation and robots, are starting to get the devotion of farmers due to the intensifying demands and labour shortages seen globally. For data collection and data exchange in the IoT, wireless technologies are crucial. Wired transmission is challenging to implement in that environment given the features of different fields in agriculture. As a result, field agriculture uses WSNs technology more often than cable transmission. Using automation and IoT technology, Gondchawar & Kawitkar (2016) planned work on IoT-based smart agriculture aimed to make agriculture smart. The utilisation of GPS-enabled intelligent remote-controlled robotic devices is anticipated for the purposes of weed removal, chemical application, and humidity sensing. These devices integrate proficient control mechanisms, advanced decision-making capabilities, precise watering techniques informed by real-time field data, and effective warehouse management strategies.

The management of all activities will be facilitated by smart device, which will establish communication with various sensors, ZigBee modules, cameras, and actuators in order to execute these operations. In order to monitor the crop field, Rajalakshmi & Mahalakshmi (2016) used soil humidity sensors, temperature and humidity sensors, light sensors, and a computerized irrigation system. Sensor data is encoded in JSON format and wirelessly delivered to the web server in order to maintain the server database. When an agricultural field's temperature and moisture content are threatened, the irrigation system will automatically activate. Notifications are sent to farmers' mobile devices on a regular basis, allowing them to check on the status of their fields remotely. This methodology was 92% more effective than the traditional method and will be more useful in locations with lack of water. According to Kassim *et al.* (2014), the implementation of WSN in SA maximises the utilisation of water and fertiliser in irrigation while also boosting crop yield. IoT-based sensor applications in Smart Agriculture for soil moisture, temperature, irrigation etc. are presented in Table 2.

Remote Sensing for agriculture: For the last two eras, Remote sensing applications have been used extensively in agriculture to assess plant health, estimate yield and crop loss (%), control irrigation, identify crop stress, detect weeds and pests, forecast weather, and gather agricultural phenological data, among other things. Considerations for remote sensing platforms for spectrum pictures include airborne, satellite, and unmanned aerial vehicle (UAV) platforms (Rudd *et al.,* 2017).

Satellite-Based Platforms: The space-borne programme is considered the most reliable platforms for Remote Sensing. Examples of these platforms include spacecraft rockets, and space shuttles. Based on their orbits and timing, space borne platforms are grouped. High spatial resolution is one of the benefits of satellite-based remote sensing, making it promise for the extraction of large amounts of broadcasting data. The illustration obtained by satellite programmes are stable and free of interference, typically introduced during image capture owing to interference. The primary issue with satellite-based platforms, meanwhile, is the expensive price of high spatial resolution imagery. The another issue is that they have a rigidly set timetable, making it impossible to collect data at crucial times. The other major issue is satellite programmes that are so sensitive to climate, if it's gloomy out, the graphic that is collected will have less information in it. The most regularly used satellite platforms for obtaining hyper spectral imagery are Quick Bird, Landsat-8, and Sentinel.

Airborne-Based Platforms: The term "Airborne" or "Aerial Imagery" refers to imagery captured by manned aircraft. Cameras or imaging systems are manually operated on the aircraft. A multispectral or hyperspectral imaging system generally consists of more than one camera, processor system, along with display to gather and show data in real time. Smart agriculture has made heavy use of airborne multispectral imaging systems since the 1990s because of their inexpensiveness, excellent resolution, speed, and capacity to gather data in spectrum ranges that are equivalent to those of traditional satellite sensors (Mausel *et al.,* 1992, King, 1995). In United States alone, there are hundreds of agricultural aircraft that are employed for production and protection of crop products. Aerial imaging equipment carried by these planes may monitor crop development, detect agricultural pests (such as bugs, diseases, and weeds infestation), and assess the efficacy of both ground-based and airborne applications.

Unmanned Aerial Vehicle (UAV)-Based Platforms: Satellite and airborne platforms provide a dynamic alternative to UAV platforms, which are relatively adaptable and inexpensive. A standard platform for an unmanned aerial vehicle (UAV) contains a number of sensors mounted to it, in addition to a communication and navigation system. UAVs are frequently constructed with an autonomous drone system that is outfitted with sensors and cameras for the purpose of monitoring the height and overall health of crops. A wide range of Unmanned Aerial Vehicle (UAV) models have been developed, with fixed-wing and multirotor platforms being the prevailing options within the UAV domain. Choose the right and proper UAVs based on the farm's agriculture. The aforementioned UAVs and remote sensing methods assist farmers in taking the proper actions at the proper time to safeguard the crops against illnesses. The Unmanned Aerial Vehicle (UAV) based approach is illustrated for smart agriculture monitoring in Figure 1. Additional benefits of the UAV for low-altitude remote sensing include strong mobility, simple construction, and high-resolution image acquisition (Zhang *et al.,* 2021, Delavarpour *et al.,* 2021). Agricultural fields can also be sprayed with fertiliser and pesticides using the unmanned aerial vehicle (Rahman *et al.,* 2021). A huge number of geographical photographs with a high resolution were taken with the UAV in order to categorise and identify the leaf spot that was present on the banana. This contributes to the overall improvement of the algorithm's efficiency (Calou *et al.,* 2020). Pests and insects in agricultural crops are observed through quantification, prediction, identification, and classification. It determines the severity of the yellow Sigatoka attack using aerial photos taken by UAV and DIP (digital image processing). It will serve as a different approach for determining the damage in the field (Calou *et al.,* 2020). The classification of soybean pest photos received from the UAV is assessed using deep learning architectures. The experimental outcomes demonstrated that, in comparison to other methods, deep learning architectures trained with fine-tuning can result in greater classification rates, with accuracies as high as 93.82%. The findings show that the examined architectures can help experts and farmers manage pests in soybean fields (Tetila *et al.,* 2020).

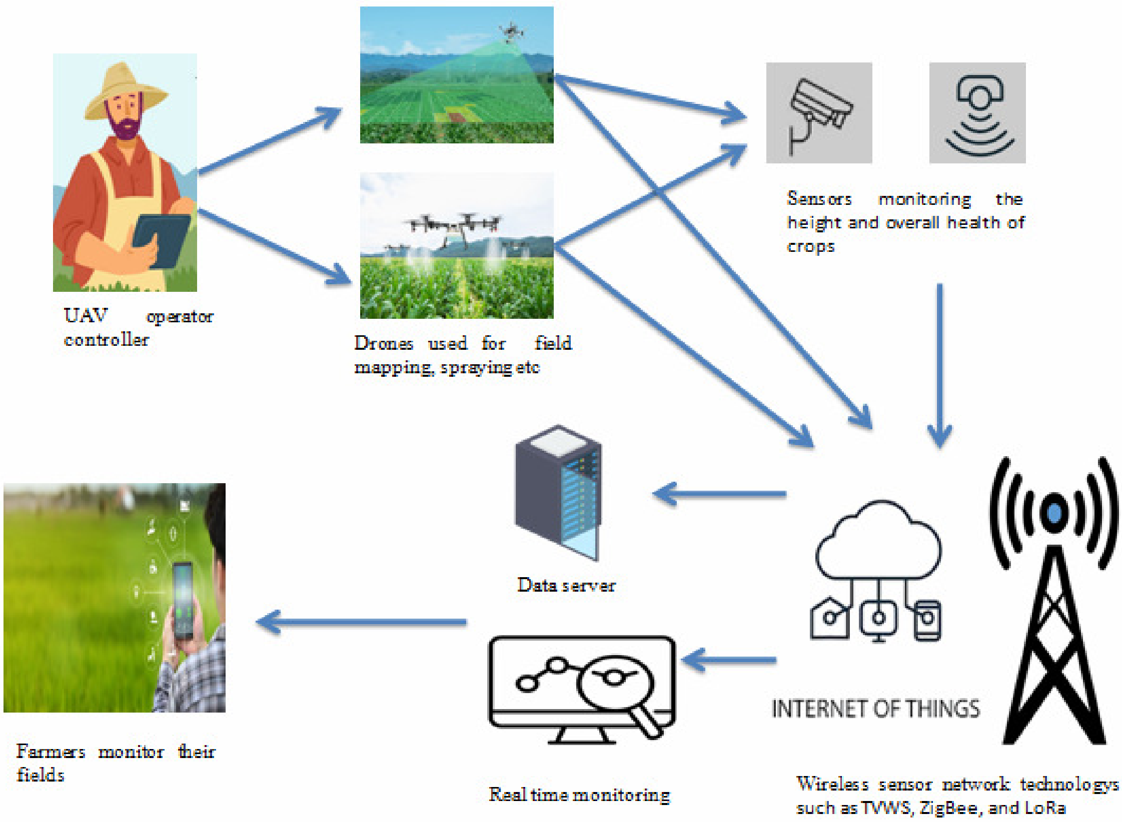

Fig. 1 : UAV operating system

Agricultural robots; Over the past decade, agricultural robots have drawn a lot of interest and are now widely regarded as one of the most promising paths towards a more productive and sustainable agriculture sector. Agricultural robots are intricate systems and automatic navigation is primary capability for Autonomous agricultural robots (Gan and Lee, 2018). Agricultural robots and related technologies are required for various activities in smart agriculture, like harvesting fruit, monitoring crop productivity (Idoje *et al.*, 2021), spraying, disease detection, and weeding (Benos *et al.*, 2022). Agri-robotic systems offer a plethora of new prospects that will aid in the transition to net zero agriculture. (Pearson *et al.*, 2022).The overall application of IoT based agricultural robots is shown in Figure 2.

A vision-based weeding robot with spraying system for weed management in a lettuce field was proposed by Raja *et al.* 2020 based on a crop signalling concept. According to experimental findings, 98.11% of sprayable weeds were found, while crop recognition accuracy was 99.75% (Raja *et al.*, 2020).In row-transplanted paddy fields, Adhikari *et al.*, 2019 suggested a convolutional encoder-decoder network-based system for distinguishing between weeds and crops. Luo *et al.*, 2020 introduced Faster Region Convolutional Neural Network (Faster-RCNN) to improve the performance of machine vision in peach tree detection for weeding robot and showed that the average detection precision rate was 86.41%.Based on deep learning technology, Quan *et al.*, 2022 created a new vertical rotating intra-row robotic weeding system for maize. Results of the trials revealed that the crop detection rate was 98.50% and the weed detection rate was 90.9%.

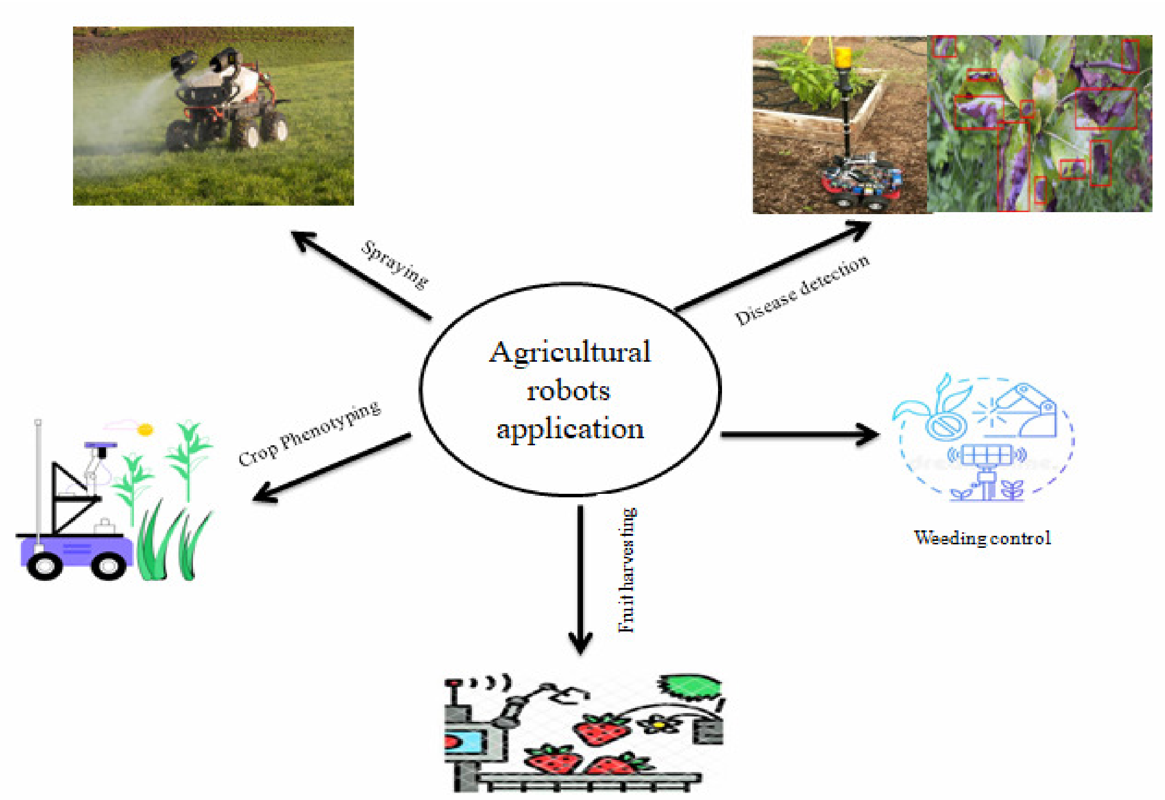

Fig. 2: Agricultural robotic application

Plant categorization requires phenotyping robots to assist measurements of certain features such as canopy-related characteristic detection, such as stem diameter (Vijayarangan *et al*., 2018) and plant height (Bao *et al*., 2019). Kang *et al*., 2020 created an intensive neural network to aid robotic apple picking by detecting and grasping fruit in real-time utilising a computer vision system. Ogorodnikova and Ali (2019) developed a method for identifying mature tomatoes in a controlled environment setting using a harvesting robot's machine vision system which transformed RGB colour images to HSV in order to isolate the mature tomato from the green background, using an image processing technique. Bai *et al*., 2023 proposed a unique vision algorithm based on the shape and growth characteristics of clustered tomatoes for target identification and picking point localization. The recognition time was less than one second, and the recognition model's precision, recall, and accuracy were all up to 100% (Bai *et al*., 2023).

Data analytics, Processing and storage in smart agriculture

Massive volumes of data are produced by the IoT, and data analytics can be used to analyse data from many types of network sensors, forecast environmental trends, and develop data-driven solutions. IoT data can monitor several parts of a field, including irrigation systems, and alert farmers to illnesses and unfavourable weather situations like flooding or drought (Lee *et al*., 2017). Figure 3 depicts how data analytics are used to carry out smart agriculture;

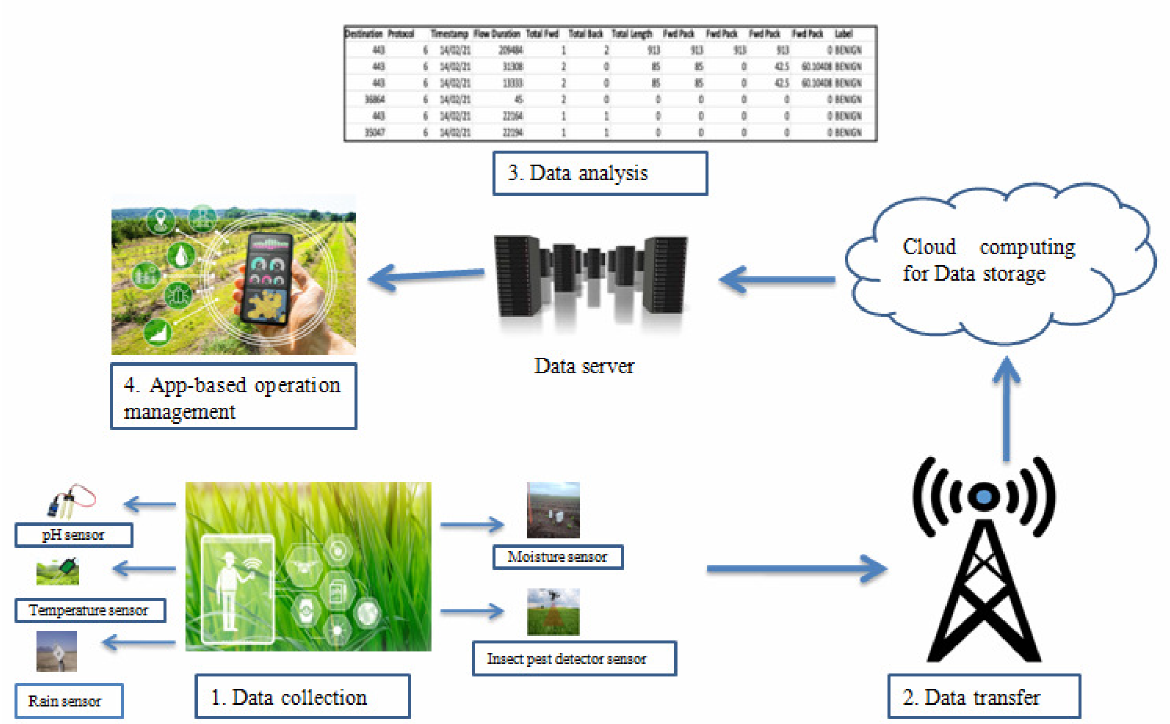

Fig. 3 : Data analytics operation in smart agriculture

Data analytics can be divided into the following categories depending on the needs of IoT applications:

i. Device-level data analytics (Safa & Pandian, 2021)

ii. Big-data analytics (Zikria *et al.*, 2021)

iii. Real-time data monitoring (Zikria *et al.*, 2021)

iv. Image data analytics

Device-level data analytics is the process of statically analysing data that has been temporarily stored in memory (Safa & Pandian, 2021). Big-data analytics is delicate process for analysing massive volumes data to extract data that may help businesses make wise business decisions, such as variations, market dynamics, and consumer preferences (Zikria *et al.*, 2021). Real-time monitoring method applies logic and statistic data to produce insights that may be utilised to make quicker and more informed decisions. Real-time analytics basically refers to the practise of performing analyses as soon as new data becomes available for some circumstances (Zikria *et al.*, 2021). Several applications of image data analysis have been utilised extensively in agriculture, including weed identification, irrigation, fruit quality evaluation, and disease identification in leaves, stems, and fruits. To increase the effectiveness of crop production, image processing and IoT have recently been applied in agriculture. Cloud computing is used to analyse and store the data. An automated self-decision framework based on data analysis can be utilised to alter the environmental conditions. In addition, a warning signal may be issued to farmers in case extreme conditions occur or a bug is discovered in the warehouse.

Applications of WSN in Smart Agriculture

WSNs are currently used in the agricultural industry for a variety of purposes. Smart pest control, smart fertilisation, smart irrigation, and monitoring of greenhouses are a few very popular applications.

Smart water management: Use of numerous sensors, IoT can effectively regulate water management, thereby reducing water waste. The water level in the tank can be monitored with the help of sensors, and data can be uploaded to the cloud and accessed from a mobile app. The water level may be checked by farmers using their smartphones. Using this method, the motor can be set to operate without human intervention. The motor will begin running when the water level drops and stop when the water level rises too high. Up to 50 percent of this water is wasted in over watering due to flaws in traditional irrigation methods and systems (Sheng *et al.,* 2013).

Smart Irrigation Systems: The implementation of developing Internet of Things technologies anticipated to affect the current state of crop irrigation practises. Crop water stress index (CWSI)-based irrigation surveillance is one example of an Internet of Things-based strategy that has the potential to greatly improve agricultural productivity (Zhang *et al.,* 2018). In smart irrigation, the amount of water is adjusted based on the actual needs of the plant. It has the greatest influence on crop output, expenses, and health of any agricultural input. Two sensors soil humidity sensor and temperature and humidity sensor were utilised in smart irrigation system that was demonstrated. The environmental conditions were monitored by the temperature and moisture sensor, while the soil moisture sensor measured the soil's water content. The Raspberry Pi was linked with both water sensor network and supply system. A smartphone app for remote surveillance and water supply regulation was developed to make it possible to regulate water flow in both manual and computerised ways (Akubattin *et al.,* 2016). Many academics have created power-efficient systems because power is a major challenge in IoT-based programmes. A wireless sensor network demonstrates power-efficient irrigation technique for cultivated crops that effectively managed water usage based on environmental factors (Nikolidaki *et al.,* 2015). Based on historical data as well as sensor-measured humidity, temperature, and wind speed, this system calculated the amount of water required for typical irrigation.

Mapping and monitoring: Agricultural businesses can save time and money by making more informed decisions with use of IoT data in field of organisation, management, and interaction with business partners. RFID and GPS used to create a detailed map of farm's growing circumstances, including the presence or absence of fertilisers, pesticides, and other chemicals. A GPS device is used to track various agricultural metrics and locate the exact position of an agricultural region using wireless network access. Architecture was created by Satyanarayana & Mazaruddin (2013) to track soil structure and condition remotely in accordance with crop cultivation requirements. In order to monitor and acknowledge real-time data processing, ZigBee is connected to other devices via WSN, including CMS, GSM, and GPRS. When unforeseen events occur, the GPS system notifies the farm manager via a communication link with the ARM or SMS so that the farmers can take appropriate action.

Smart Fertilization System: Fertiliser, whether synthetic or natural, boosts plant growth and output. Fertiliser is usually sprayed manually. However, optimal fertilisation requires sensing to find the exact location, chemical components, and amount of fertiliser needed. To increase yield, fertilisers must be applied precisely (Cugati *et al.,* 2003). Since the last decade, researchers have proposed a variety of fertilisation methods employing WSN and IoT. Inoue (2020) was presented a robotic fertilisation system that assesses soil fertility in real time via sensors. The system consisted of the user's input, the system's output, and a means to help in making decisions. The optimal amount of fertilisers required for plant growth was determined by the decision assist unit using real-time sensory information from the sensors.

Advanced Pathogen and Pest Detection Technology: Pest infestations are a major contributor to the agricultural sector's miserable output. These pests cause a number of significant plant diseases that limit the growth of the affected plants. However, disease prediction gives farmers an early heads-up so they can take the proper action to stop the disease in its tracks. Electronic devices used in pest control systems make it possible for people to spot traps within a certain range of these gadgets (Mahlein *et al.,* 2012). Electronic devices are sensors that can determine environmental characteristics for additional investigation. Agricultural early disease detection and pest management systems have been the subject of extensive research employing more sophisticated and advanced technologies (Mahlein *et al.,* 2012). In order to reduce the overuse of fungicides and pesticides, an Internet of Things-based system for predicting plant diseases and pests was introduced. To determine whether there is a relationship between pest growth and weather, weather condition monitoring sensors are utilised. These sensors measure temperature, dew, moisture, and wind speed. Crops integrated with sensor technology facilitate the collection and transmission of data to cloud-based platform. Through this system, farmers are promptly notified of the alarming presence of significant insect infestation affecting their crops (Lee *et al.,* 2017).

The majority of Smart Agricultural technologies have predominantly depended on two approaches: the Internet of Things (IoT), which involves the utilisation of numerous sensors to evaluate the health of crops, and remote sensing, which involves assessing the health of crops by doing basic calculations on spectral pictures. Based on a few characteristics, such as the sensors used in various apps, the availability of web or mobile services, etc., we may compare crop health monitoring software.

Important concerns relating to WSN issues

Since a few decades ago, SA has been utilised to increase crop output with less expense and labour, but farmers have been slow to adopt these cutting-edge practises for the reasons or difficulties listed below:

Equipment cost: The majority of SA's support comes from hardware, which includes sensors, wireless nodes, drones, spectral imaging sensors, and other devices that are used to evaluate a number of factors in real time. The high cost of development, maintenance, and deployment is just one of the constraints these sensors face. Smart irrigation systems, which need inexpensive hardware and sensors, are some technologies that are ideal for tiny arable land and are cost-effective. The high installation costs of drone-based crop health monitoring systems, however, make them only practical for huge arable land.

Climate Change: Climate change is a major factor influencing the reliability of sensor data. Sensors deployed in the field are highly attuned towards their immediate surroundings and react quickly to changes in humidity, temperature, wind speed, light intensity, and so on. Atmospheric disturbances can cause interference in wireless communication channels, which can disrupt data transmission between wireless nodes and the cloud. Drones, satellites, and aeroplanes all rely on platforms that can be affected by the weather. Cloud pollution and other natural aerosols have an impact on the imagery that these systems capture.

Literacy rate and communication networks: The adoption rate in SA is significantly impacted by literacy. Farmers cultivate crops based on their experience in developing nations with high illiteracy rates. They lose production because they don't use modern agricultural technology. Farmers need training to understand the technology, or else they will have to rely on outsiders to answer their questions and solve their problems. Due to the lack of resources and access to education, SA is therefore uncommon in undeveloped regions with low literacy rates.

The speed at which devices and servers can communicate via 5G networks is 100 x that of 4G networks. Due to its increased data-carrying capacity relative to current networks, 5G technology is well-suited for the transmission of data collected by remote sensors and drones. These technologies presently being tested in Smart agricultural environments.5G communication networks are crucial for modern applications that rely on safe and quick data transport for real-time data management and decision support.

IoT data issues: Smart agriculture data issues include reliability, homogeneity, and volume.

Data homogeneity: Agricultural data can be lost due to factors such as malfunctioning machinery, network outages, botched post-processing, and the introduction of harmful insects or diseases. Missing data causes inaccurate computations and hinders agricultural IoT applications.

Data Reliability: The most common causes of missing data in agriculture include mechanical breakdown, power outage, bad weather, incorrect data labelling, and computational error. Smart agriculture uses data mining for crop safety, irrigation forecast, and pesticide reduction. Noisy and anomalous data hinder smart agriculture data mining. Thus, noise must be managed using proven methods.

Data Volume: Big data also causes heterogeneous data. Agricultural information is collected by monitors, unmanned aircraft, sensors, and RFID tags. Due to the heterogeneity of huge data sets, frameworks can be used to lessen the resources required for their analysis.

Smart Agriculture security risks related to Internet of Things (IoT)

When data processing, administration, and storage are integrated with Internet access, a number of problems and security risks arise. Smart systems are made up of various hardware and software components from various manufacturers that are put between growing regions and the cloud. These particular qualities could lead to many security lapses and mishaps that jeopardise the smart system (Zhao& Ge2013). Research has indicated that Internet of Things (IoT) devices utilised in the domain of Smart Agriculture are vulnerable to physical manipulation, encompassing incidents such as theft, intrusions by rodents and livestock, as well as alterations in physical location or connectivity (Demestichas *et al.,* 2020). The perception layer is primarily concerned with physical elements like sensors and actuators. Physical equipment may become unreliable due to malicious software, criminal conduct (intentional or not), or human error. Due to their limited memory, networking capabilities, and low energy consumption, IoT devices find it difficult to implement extensive and intricate algorithms. On the gateway, it is possible to suffer from routing assaults, DOS threats, and congestion threats. The bulk of modern Smart Agricultural apps are built on IoT technology, thus it's vital to highlight that they could immediately inherit its security flaws. In procedures like Message Queuing Telemetry Transport (MQTT)and Constrained Application Protocol (CoAP),security elements are deactivated by default; the operator must enable them in accordance with the project's goals (Goap *et al.,* 2018).

Conclusion

In the pursuit of augmenting agricultural yields, contemporary farmers are increasingly adopting methodologies underpinned by "Smart Agriculture" (SA), leveraging cutting-edge technologies such as Wireless Sensor Networks (WSN), Internet of Things

(IoT), cloud computing, Artificial Intelligence (AI), and machine learning. Empirical studies consistently underscore the profound impact of SA-based practices on both environmental sustainability and operational efficiency. Central to the objectives of SA is the provision of decision-support systems predicated on a comprehensive array of crop-related variables, encompassing soil nutrient levels, soil moisture content, wind velocity, light intensity, ambient temperature, humidity, and chlorophyll concentration. These systems aim to optimize yield while concurrently minimizing resource inputs, including water, pesticides, and fertilizers. A pivotal aspect of resource optimization within SA frameworks involves the utilization of prescription maps, facilitating pre-emptive resource allocation tailored to the exigencies of crop health at specific temporal junctures. The deployment of wireless field monitoring obviates the necessity for manual intervention, affording users real-time oversight of agricultural productivity fluctuations. However, the development and implementation of such systems are beset by a myriad of challenges. Notably, the proliferation of devices generating voluminous data streams necessitates rigorous attention to data security considerations. Safeguarding data integrity, from inception through decision-making processes to storage within the agricultural ecosystem, emerges as a critical imperative.

Table 1: IoT technologies of several kinds in Smart Agriculture

IoT technology	Implementation in Agriculture	Agriculture's Advantages
WSN: Sensor capable of radio communication	Combining sensors to track numerous physical properties	Simple management and collecting of data from sensors
Cloud computing: Internet-based computing that uses the cloud	Provides computers and other devices with pooled processing resources and data as needed.	Simple data gathering and management from cloud computing services like maps of agricultural fields, cloud storage, etc.
Big Data Analytics: large-scale data collections analysis	This tool is employed for the examination of various data sets, including but not limited to fertiliser requirements, crop analysis, market demands, and crop inventory management. Subsequently, a forecast is generated employing data mining methodologies, and the agriculturalist obtains the pertinent information through a mobile application.	Describe new generation of processes designed to assure better information gathering, discovery, and/or analysis so that farmers and related organisations can profit financially from huge quantities of very large amounts of information
Communication Protocols: IoT system core components that enable connectivity.	Various data interchange formats can be exchanged across the network	Massive amounts of data easily collected and managed from sensors, cloud storage, and other sources
Artificial intelligence: revolutionising the agricultural industry.	By producing healthier crops, controlling pests, monitoring the soil, and in a variety of other ways, it benefits farmers.	AI has significantly improved real-time monitoring, production, harvesting, processing, and selling in the agricultural sector.

Table 2: IoT-based sensor applications in Smart Agriculture

Sensors	Application	Working procedure	Reference
DHT11 Sensor	Evaluates field's temperature and humidity level	The sensors in the firmware-based smart irrigation system are connected to the Arduino, and sensor values are continuously tracked. A GSM sim900A module transmits readings to the farmer's mobile device, which informs farm status.	Sudarshan *et al.,*2019
DHT22 sensor	Temperature and relative humidity are measured.	It measures the air around it using a thermistor and a capacitive moisture sensor and sends a digital signal to the Arduino data pin.	Laskar *et al.,* 2016
SEN0193: Soil Moisture Sensor	Utilised to assess soil moisture levels and control irrigation in greenhouses	The Soil Moisture Sensor measures dielectric permittivity via capacitance. Soil dielectric permittivity depends on water content. The soil's dielectric permittivity and water content determine the sensor's voltage.	Ganesh *et al.,* 2018

YL69	Used to detect moisture content of soil	The 16 Channel Analogue Multiplexer with Sensors connects the water level and soil moisture level. The maximum voltage needed for both the water level sensor and the soil moisture sensor is 5 V. To gauge the amount of moisture in the soil, this sensor can be buried underground.	Asnawi *et al.,* 2019
10HS sensor	Measure soil volumetric content		Yadav *et al.,* 2020
STM-100, TMH-2000	Used to measure real-time soil moisture		Liao *et al.,* 2021
BH1750: Light sensor	Used to Monitors light intensity and conducts studies on how light intensity affects greenhouse temperature.		Jayasuriya *et al.,* 2018

Author contributions

SS wrote the original draft. BG critically analyzed the manuscript and edited it for language. All authors contributed to the article and approved the submitted version.

Conflict of Interest: None

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