AGRICULTURE 5.0

Artificial Intelligence, IoT and Machine Learning

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CRC Press
Taylor & Francis Group

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CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business

First edition published 2021
by CRC Press
6000 Broken Sound Parkway NW, Suite 300, Boca Raton, FL 33487-2742

and by CRC Press
2 Park Square, Milton Park, Abingdon, Oxon, OX14 4RN

CRC Press is an imprint of Taylor & Francis Group, LLC

Library of Congress Cataloging-in-Publication Data

ISBN: 978-0-367-64608-0 (hbk)
ISBN: 978-0-367-64610-3 (pbk)
ISBN: 978-1-003-12543-3 (ebk)

Typeset in Times New Roman
by MPS Limited, Dehradun

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List of Abbreviations

ADC	Analog to Digital Converter
ADSS	Agricultural Decision Support System
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ANT	Adaptive Network Topology
APIs	Application Programming Interface
BLE	Bluetooth Low Energy
CAGR	Compound Annual Growth Rate
CDAC	Center for Development of Advanced Computing
CGIAR	Consultative Group on International Agricultural Research
CIAE	Central Institute of Agricultural Engineering
CMOS	Complementary Metal Oxide Semiconductor
CPS	Cyber-Physical System
CPU	Central Processing Unit
DARE	Department of Agricultural Research and Education
DARPA	Defence Advanced Research Projects Agency
DPM	Dynamic Power Management
DSN	Distributed Sensor Networks
DSS	Decision Support System
DVS	Dynamic Voltage Scaling
EEPROM	Electrically Erasable Programmable Read-Only Memory
ENS	Embedded Networked Systems
FAO	Food and Agriculture Organization
GIS	Geographic Information System
GMO	Genetically Modified Organism
GNSS	Global Navigation Satellite Services
GODAN	Global Open Data for Agriculture and Nutrition
GPRS	General Packet Radio Services
GPS	Global Positioning System
GSM	Global System for Mobile
GSN	Global Sensor Networks
GUI	Graphical User Interface
HSPA	Evolved High-Speed Packet Access
IBM	International Business Machines Corporation
ICAR	Indian Council of Agricultural Research
ICT	Information and Communication Technology
IDE	Integrated Development Environment
IDSS	Intelligent Decision Support System
IEEE	Institute of Electrical and Electronics Engineers
IERC	International Energy Research Centre
IETF	Internet Engineering Task Force

IoE	Internet of Everything
IoT	Internet of Things
IoTWF	IoT World Forum
IP	Internet Protocol
IPFT	Intelligent Precision Farming Technology
IR	Infrared
IR	Infrared
ISM	Industrial, Scientific, and Medical
ISO	International organization of Standardization
ISPA	The International Society of Precision Agriculture
ISRO	Indian Space Research Organisation
IT	Information Technology
ITC	Indian Tobacco Company
ITU	The International Telecommunication Union
LAN	Local Area Network
LCC	Leaf Colour Chart
LED	Light Emitting Diode
LoRa	Low Range
LoWPAN	Low-Power Wireless Personal Area Network
LTE	Long-Term Evaluation
M2M	Machine to Machine
MEMS	Micro Electro Mechanical Systems
MIT	Massachusetts Institute of Technology
MiWi	Microchip Wireless
ML	Machine Learning
NABARD	National Bank for Agriculture and Rural Development
NAIP	National Agricultural Innovation Project
NASA	National Aeronautics and Space Administration
NBSSLUP	National Bureau of Soil Survey and Land Use Planning
NiCd	Nickel Cadmium
NIMS	Networked Info Mechanical Systems
NIST	National Institute of Standards and Technology
NNI	National Nanotechnology Initiative
NOAA	National Oceanographic and Atmospheric Administration
ODLT	Open Distributed Ledger Technology
OSI	Open System Interconnection
PA	Precision Agriculture
PDCSR	Project Directorate for Cropping Systems Research
PF	Precision Farming
PFDCs	Precision Farming Development Centres
RF	Radio Frequency
RFID	Radio-Frequency IDentification
ROM	Read Only Memory
RS	Remote Sensing
R&D	Research and Development

SHF	Super High Frequency
SMS	Short Messaging Service
SOSUS	Sound SUrveillance System
SPAD	Soil Plant Analysis Development
SSCM	Site-Specific crop management
UAV	Unmanned Aerial Vehicle
UHF	Ultra-High Frequency
UN	United Nations
USD	United States Dollar
USN	Ubiquitous Sensor Network
VRA	Variable Rate Application
VRT	Variable Rate Technology
W3C	World Wide Web Consortium
WiFi	Wireless Fidelity
WiMAX	Worldwide Interoperability for Microwave Access
Wireless HART	Wireless Highway Addressable Remote Transducer Protocol
WSN	Wireless Sensor Networks

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1 Introduction to Precision Agriculture

1.1 HISTORY OF PRECISION AGRICULTURE AND ITS GLOBAL ADOPTION

Precision farming was adopted by US agriculture in the 1980s at a sluggish rate of 10 to 15 years due to doubt in profitability at that time, as no legitimate pieces of evidence were present and the adoption of this innovation was uneconomical. Some specific reasons include the lack of genuine information at that time, farmer attitude, economic constraints in acquiring technology, and the technology itself. Later, it was discovered that the two major reasons were:

I. Willingness:
   Willingness is directly proportional to the availability of information about PA, precision in information, and the probability of positive results.
II. Ability to Adopt:

Early in the year 2000, it was identified that the adoption of precision farming was related to:

a. The degree of relevance between the existing problem and the technology
b. Ease of handling the technology
c. Most importantly, the profit related to the aforementioned adoption

During the early stages of implementing precision farming, improving efficiency was the only motivating factor and, of course, this was not sufficient. Batte and Arnholt investigated that profit that was related to PA was the biggest contributing factor [1]. During the first ten years, the 21st-century exponential rate for acceptance of PA was observed among producers as well as commercial businesses.

The reason for this rapid growth in adoption during the last 15 years is related to certain factors:

1. In terms of efficiency, productivity, and profitability executed in an eco-friendly manner, nutrient management research has enabled development.
2. The affordable pricing of commodities led to high net profits and large investments in advanced technologies.
3. Auto-guidance systems not only improved the farming efficiencies but also reduced the manual efforts of farmers.

4. There was an increase in the number of skilled people who had knowledge about both agricultural and technological domains.

The abovementioned factors only constitute a few of the reasons for the adoption of PA in the past 15 years. However, there was a gap that needs to be bridged among different sectors. The acceptance of PA has boosted due to the collaborative and synchronized efforts of industries, researchers, institutions, and the media. Global extensive research is proving beneficial and is significantly changing the agricultural domain [2].

1.2 PRECISION AGRICULTURE – INTRODUCTION

This book is aimed to provide a deeper insight into precision agriculture by discussing almost all of the techniques and tools that are currently used all over the world.

India is a vast land with a diverse climate and has an edge in producing a multitude of vegetables and crops throughout the year. According to the Ministry of Agriculture, India has achieved the second position in terms of the production of fruits and vegetables worldwide, following China (Reported by *Horticulture at a Glance* 2015). The Indian population is completely dependent on the production of cereal crops, fruits, vegetables, and milk, thus turning the country into a farming powerhouse globally. Nonetheless, we are still lacking in terms of productivity, focus, competition, and zoned agricultural sector. The requirement to remove these limits is quite simple: we need to adopt and promote the use of new technology and sciences that will be achieved by rigorous research in the field of agriculture [3]. The dearth of awareness as well as inadequate utilization of technology and traditional mechanisms for handling agricultural practices and constraints have negatively affected production all over the country.

The introduction of the latest and most innovative techniques, concepts, methodologies, and technology to replace conventional agricultural ways, thus making it sustainable is called Precision Agriculture (PA). It is focused on maximizing production while using the least amount of resources while causing minimum impact on the environment by judicious irrigation and an adequate quantity of pesticides and fertilizers. PA critically depends upon factors such as information, technology, and management which have equal importance and accords numerous benefits on crops [4]. Nowadays, we become increasingly familiar with the term, and there has been a progressing trend toward this field. When agricultural practices are executed rather efficiently, such as when the proper amount of materials required (e.g. fertilizers, pesticides, nutrients, water, etc.) are supplied at the proper location and at the correct time to boost production, to grow profits, to directly promote soil health, and to indirectly increase water quality and farmer health while reducing environmental wastes is termed as precision agriculture [5]. In India, PA is still in its infancy, and significant work is currently proceeding in this field.

1.2.1 Foreign Perspective

The first definition of PA was given by the US House of Representatives (US House of Representatives, 1997) [6].

> *Precision agriculture is an integrated information- and production-based farming system that is designed to increase long-term, site-specific, and whole farm production efficiency, productivity, and profitability while minimizing unintended impacts on wildlife and the environment.*

According to Gandonou [7]:

> *PA can be defined as a set of technologies that have helped propel agriculture into the computerized information-based world and is designed to help farmers get greater control over the management of farm operations.*

As reported by the Second International Conference on Site-Specific Management for Agricultural Systems that was held in Minneapolis, Minnesota, in March 1994 [6]:

The precision farming system within a field is also referred to as site-specific crop management (SSCM).

As stated by the National Research Council, Italy 1997 [6]:

> *SSCM refers to a developing agricultural management system that promotes variable management practices within a field according to site or soil conditions.*

The genetic improvement, agrochemical practices, irrigation, and farm machinery have been successful in improving productivity, but this is not significant enough to meet the continuously growing demand due to population expansion. Increased demand poses a threat to the environment as well as food security all over the world. Numerous innovative attempts have been pursued to enable sustainable crop production. Precision farming system (PFS) was one of the efforts that were undertaken during the early 1990s. This made its appearance in various forms, depending on the knowledge and technology that were available during its time. PFS was the combination of the latest technology and the mechanization of the agro-sector. PFS made a sharp turn with the introduction of electronic information technology which enabled the collection, processing, and analysis of the data from different sources streamlined for decision-making. PFS has gained the platform due to a decline in the rates of agricultural products and increased production. Even the National Aeronautics and Space Administration (NASA) has shown interest in PA, hence proving the importance of its enactment [6]. Furthermore, precision farming technology (PFT) acts as a reliable base for making site-specific management (SSM) decisions. There has been an enormous demand for information about technologies that are used to manage agricultural production systems with the introduction of:

1. Yield monitors
2. Global positioning systems
3. Improvements in computing power and data management [8].

This emphasizes the use of technologically sophisticated equipment and promotes research and development in agronomy and crop and soil science in providing vital information and supporting decision-making for variable application of inputs at the local levels too [9].

1.2.2 Indian Perspective

Below is a definition of PA that is accepted in India:

> *Precision agriculture, satellite farming, or site-specific crop management is farming based on observing, measuring, and responding to inter- and intra-field variability in crops.*

Another interpretation is the following:

> *PA is an information- and technology-based farm management system to identify, analyze, and manage variability within fields for optimum profitability, sustainability, and protection of land resources.*

The succeeding meaning also defines PA:

> *PA is the precision application of technologies and input based on soil, crop weather, and market demands to maximize sustainable productivity and profitability.*

Finally, another acceptable definition is in the next paragraph:

Precision forming is generally defined as an information and technology best for the management system to identify, analyze, and manage variability within fields for optimum profitability, sustainability, and production of land resources.

PA in India is different from the traditional models because the input, in this case, is of optimum quantity and has increased yield comparatively. The main components of PA are namely: information, technology, and management from a comprehensive system that improves the efficiency of production, its quality, crop efficiency, reduces energy utilization, and safeguards the environment. PA proves naturally beneficial for small farmers in developing countries due to more yield with minimum input.

Furthermore, the masses should be environmentally conscious while adopting PA. Hence, there is a demand to alter conventional agricultural management so as to make sustainable conservation of natural resources (i.e. water, air, and soil quality). The concept of five "**Rs**" in the PA explain further [10], [11]:

a. **R**ight input (of fertilizers and pesticides)
b. **R**ight time
c. **R**ight place
d. **R**ight amount
e. **R**ight manner

This is called site-specific management. Market-based global competition in agricultural products is the main challenge of the traditional agricultural systems, so the scope of PA lies in this aspect [12]. In PA, we need to accumulate huge data that comes from a myriad of sources while mapping the factors of soil, crop, and environment of the field. Therefore, PA is said to be "information intense". Figure 1.1 shows the information flow below.

The data is acquired from the internal factors (e.g. soil, crop, environment) and is then compounded by expert knowledge (e.g. the site data manager) as well as data from the existing market and the metrological department. The development of data integration tools, expert systems, and decision support systems makes the administration of this huge data more convenient (Sigrimis et al., 1999). There should be provisions in PA for the standardization of data formats [9].

Some basic steps involved in PA are illustrated through the succeeding flow chart [13]:

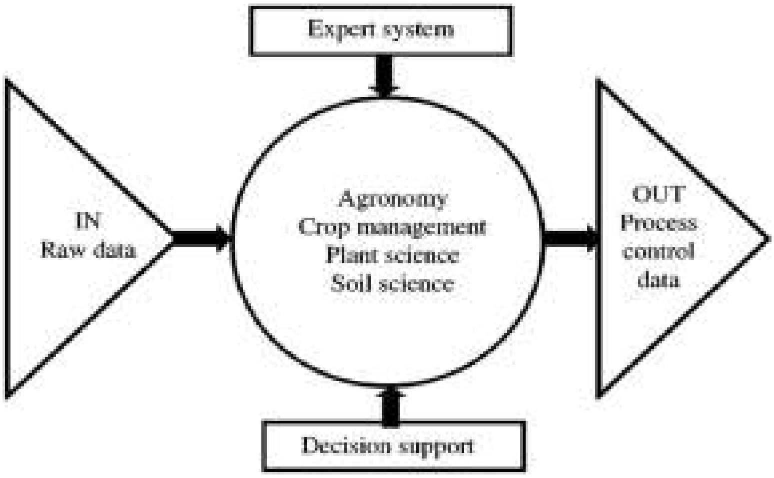

FIGURE 1.1 Information Flow in Precision Agriculture

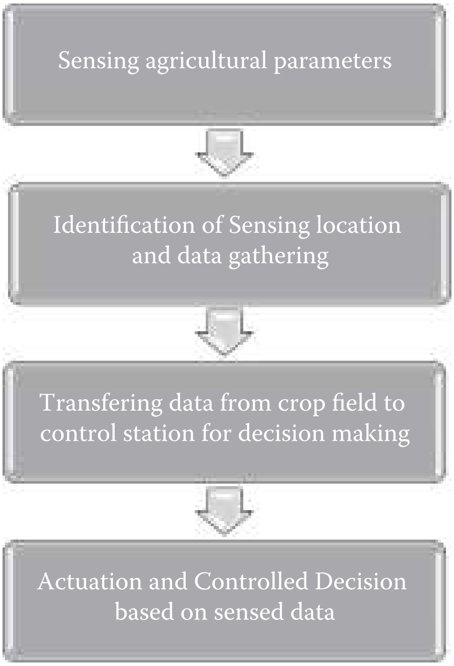

FIGURE 1.2 Basic Steps Involved in PA

1.3 NEED AND SCOPE OF PRECISION AGRICULTURE

The population of India is growing rapidly, and unless affordable technologies and solutions are developed for farmers and applied to minimize crop deficiency, food security would be a challenge [4]. Significant improvements include the minimal use of water, fertilizers, pesticide, insecticide, and herbicides along with the specialized equipment necessary. The earlier concept of farming was based on the assumption of hypothetical average conditions, which was far from the actual situation, so there was a need to be precise in order to identify the site-specific differences within fields and modify management plans accordingly (Figure 1.1). The variations in the yield across the whole area of a farmer's administration are usually noted. These are actually the results of soil properties and environmental characteristics along with the management strategies. It was an arduous task for a farmer to retain information about the field conditions and corresponding necessary treatments which he gained through years of trial and error. Moreover, the shift in areas of cultivation made it even more difficult for the farmer to adopt the same measures that were observed through past experiences. PA has eased this problem by an automatic and simplified collection of information – analyzing data and providing results for better management decisions which are faster and quickly implemented on specific sites within large fields (Figure 1.3 [13]).

1.4 COMPONENTS OF PRECISION AGRICULTURE

Precision agriculture is hinged on the 5 R's: right input, right time, right place, right amount, and right manner [10]. For the smooth implementation of PA, these 5 R's should be fulfilled. PA is all about collecting and satisfying accurate information that is required in a number of precision agriculture tools.

On the other hand, PA is possible only due to the recent advancements in the technological arena. These technologies can interoperate to make a working precision agriculture system to assist farmers when making site-specific management (SSM) decisions and also other relevant operations. Technologies like yield monitors, global positioning systems, and more, and has thus increased the demand for the agricultural production system due to improvements in computational and data management capabilities.

Precision agriculture can also be considered as a management strategy which is an upgrade of the conventional strategies, and it uses important data for site-specific decisions that are associated with crop production. It allows for the management of spatial and temporal variability within a field, a reduction of costs, an improvement of yield quantity and quality, and a minimization of environmental impacts.

Accordingly, it can be concluded that PA has three main components:

1.4.1 INFORMATION

To achieve maximum results in PA, vital information is necessary for parameters such as crop characteristics, soil properties (e.g. topography, fertility status, texture, moisture content/retention, tillage needs, salinity, waterlogging, etc.), the incidence of pests (e.g. insects, diseases, weeds, and others), weather/climatic conditions, other biotic and abiotic stresses, plant growth response, harvest and

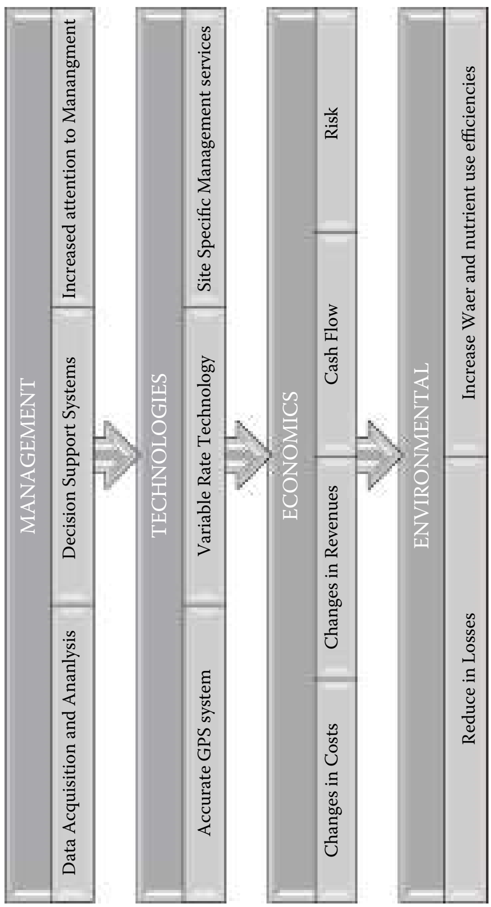

FIGURE 1.3 Considerations in Precision Agriculture

postharvest handling, marketing and market intelligence, and socioeconomic conditions of farmers, among others. The data can be used for almost all of the processes to produce a significant improvement in comparison to traditional agriculture. It can be used to create information-rich maps of the farms/villages/regions (e.g. different soil characteristics, groundwater, pest incidence, weed distribution, topography, environmental pollution, etc.). This information serves as the backbone for accomplishing site specific-decisions [14].

1.4.2 Technology

Emerging technologies work hand-in-hand with precision farming in order to keep farmers updated and to provide them with all of the associated benefits. The technologies have proven to increase production, productivity, and profitability to a compelling magnitude. The use of remote sensing and geographic information system (GIS), GPS, auto-analyzers, sensors, actuators, and computers along with appropriate software, massive storage technologies, real-time computing devices, and more can help in precisely identifying the areas of deficiencies and quantifying the analysis of the economic significance of the soil-water-fertilizer-pest-crop-related constraints beside their environmental impacts at the farm/village/region levels. These can provide important guidance for adopting the systems of integrated management of soil health, nutrients, pests, water, energy, and different crop genetic resources. By using sensors, the postharvest quality of the produce can be monitored and enhanced. Drones can be used for surveillance and spraying purposes. In addition, driverless tractors are an incredible example of PA technology. Finally, IoT systems have certainly been an advancement in PA [14].

1.4.3 Management

It is correctly spoken that, “Management is the key to success in Precision Agriculture.” Accurate management is vital for the performance of precision agriculture. Management combines information obtained with available technology into a comprehensive administration system. The user must possess sufficient knowledge to apply the aforementioned information and technology to be able to procure maximum benefits. The 5 R’s are supported by precise and competitive management. The complexity of agriculture and diverse expertise required for the development and dissemination of knowledge-intensive precision farming technologies require the multidisciplinary efforts of agronomists, plant breeders, soil scientists, agro-meteorologists, entomologists, plant pathologists, weed scientists, biotechnologists, economists, extension workers, and, of course, farmers [14].

For effective PA, there is an obligation for information management, a decision support system (DSS), and a specific precision agriculture service provider [15].

1.5 TOOLS AND TECHNIQUES

1.5.1 Global Positioning System (GPS)

The Global Positioning System (GPS) [12], [16], [17] is the most important tool in precision agriculture. It is defined as a navigation system that consists of a network of satellites that enables the identification of locations within a meter of an actual site in the field (100 m to 0.01 m) [12]. This location contains information such as latitude, longitude, and elevation of that specific portion of the field in order to identify details about crops, soil, water, obstructions, pest occurrence, weed invasion, among other relevant things at that position. A user with such a sophisticated and accurate position system has the means to handle precision agriculture. The following are some of the benefits of GPS in agriculture:

- Mapping of soil and crop measurements
- Application of inputs (e.g. seeds, fertilizers, pesticides, herbicides, and irrigation water) to target areas
- Monitoring yield
- Management of farm

1.5.2 Geographic Information System (GIS)

The Geographic Information System (GIS) is a revolutionary technology that enables work on data that is associated with a spatially mapped area on the earth. It is a database that is specially designed to work with map data. GIS is a platform to handle the compilation, storage, retrieval, and analysis of data that is related to the attributes of a particular location (i.e. spatial information). GIS software facilitates the storage and organization of data from multiple sources of site-specific and geographical data information in various layers. Each layer in GIS is termed "coverage" and consists of topologically linked geographic features (e.g. topography, soil types, surface drainage, subsurface drainage, etc.) and associated data. GIS is undoubtedly more than a mere traditional map that has the ability to provide relative solutions. Rather, it bears computing and analysis power that generates complex views of the fields and conceives valid agro-technological decisions.

GIS-systems are reliable for data synthesizing and decision-support systems in many fields; however, GIS should not be confused with the decision-making systems themselves.

1.5.3 Wireless Sensor Networks

Wireless Sensor Networks (WSN) [3] is a technology in which a number of sensors are deployed across the field as per the requirement and are consolidated in a network that provides information about various parameters in the field.

There have been advancements in the field of sensor development that have resulted in significantly more accurate sensors. Sensors are mainly used for humidity, vegetation, temperature, texture, structure, physical character, humidity, nutrient level, vapor, air, etc. in PA. These data, when processed and analyzed, give a valuable result that helps in achieving the objectives of PA [12]. The WSN has been explained in-depth in ‘chapter WSN.’

1.5.4 Agricultural Drones and Robots

Drones are versatile and have found their application in various sectors, including the agricultural arena. With the implementation of artificial intelligence (AI) in drones, their application in precision agriculture has significantly increased as it is convenient for a farmer to operate. Drones help in various operations like data collection, crop and field monitoring, disease detection, as well as many PA practices like spraying inputs, surveillance, etc.

The aim of AI has always been to minimize human efforts that are using this disruptive technology. The precision agriculture realm is one of the important fields which need automation and smart devices that can perform functions that once needed human intervention. Examples include smart tractors that are straightforwardly AI-based machines possessing multiple technologies such as sensors, radars, and GPS systems to perform the functions independent of an operator [18].

1.5.5 Satellites

Satellite data provides many advantages in precision agriculture over conventional methods, particularly in terms of timely decision-making mechanisms, spatial depiction, and coverage including cost-effectiveness. Space data is used in addressing many critical aspects such as crop area estimation, crop yield and production estimation, crop condition, deriving basic soil information, cropping system studies, experimental crop insurance, and more [19]. Satellites are also used as a management tool in the practice of precision agriculture, because satellite images are used to characterize a farmer’s fields in detail and are often used in combination with geographical information systems (GIS) to allow more intensive and efficient cultivation practices [20].

1.5.6 Precision Irrigation System

A sprinkler irrigation system that has GPS-based controllers is an example of the important tools used in precision agriculture. The Wireless Sensor Networks in these irrigation systems help to monitor soil and ambient condition along with the operational parameter of the irrigation system that includes floe, pressure levels, etc. This information helps in the precise application of the amount of water to optimize the yield.

1.5.7 Software

A variety of software is needed for a multitude of tasks in PA. Certain types of software with specific functions are listed below [12]:

- Software for mapping
- Software for variable-rate applications and map-generators
- Software to overlay different maps
- Software to provide advanced geostatistical features
- Software having statistical analysis tools

Precision farming software includes controller tools that are widely used in precision agriculture technology. IoT improves software maintenance – for example, through automatic equipment updates – and introduces new solutions for farm management, such as managing a safe-driving tractor remotely via a controller. The capacity of modern precision agriculture and IoT enables controlling dozens of equipment units simultaneously [21].

1.5.8 Yield Monitoring

In precision agriculture, yield monitoring is paramount. The yield monitoring system is a combination of various components like sensors, storage devices, user interface, computing machine, the control system for integration and interaction of these components, and more. Yield monitors are attached with equipment, such as combined harvesters or tractors, to gather a significant amount of information – specifically, grain yield, moisture levels, soil properties, and much more. This data is collected for more than ten years to provide rich, meaningful data for spatial and temporal trend analysis and management information. Yield mapping can be done with a GPS combined with the yield monitoring system [8].

1.5.9 Online Platforms

In this era of the Fourth Industrial Revolution, there is an enormous amount of information that is being administered by the government, organizations, volunteers, etc. to promote and help in the application of PA by farmers. The business sectors promote their PA equipment and software technologies through these online platforms and can also help users to find the right solutions with their tools [12].

1.5.10 Remote Sensing

Remote sensing is the art and science of gathering information about objects or areas of the real world from a distance without coming into direct physical contact with the objects under study. The principle behind remote sensing is the use of electromagnetic spectrum (e.g. visible, infrared, and microwaves) for assessing the earth's features.

Remote sensing is an important tool in PA that has shown momentous benefits in combination with GIS, GPS, satellites, etc. The following are some of the ways how remote sensing leverages the benefits of PA [16]:

- Soil mapping; climate and land characteristics determination
- Crop nutrient deficiency detection
- Vegetative analysis
- Crop yield estimation and production forecasting
- Indian crop yield forecasting
- Satellite-based agro-advisory service
- Pest management
- Assessment and monitoring
- Soil site suitability assessment
- Soil moisture estimation
- Floods assessment and monitoring

1.6 SITE-SPECIFIC CROP MANAGEMENT (SSCM)

There are various definitions of SSCM, the first is noted below:

SSCM refers to a developing agricultural management system that promotes variable management practices within a field according to site or soil conditions. (National Research Council, 1997)

The second interpretation is the following:

Site-specific crop management (SSCM) is the precision farming system within a field [6].

Another meaning characterizes SSCM:

SSCM is a form of PA whereby decisions on resource application and agronomic practices are improved to better match soil and crop requirements as they vary in the field.

Some experts believed that SSCM is not a single technology, but rather, an integration of technologies that enable the succeeding operations [6]:

1. Collection of data on an appropriate scale and at a suitable time
2. Interpretation and analysis of data to support a wide range of management decisions
3. Implementation of management responses on an acceptable measure and at the correct time

The last definition, in this case, focuses mainly on the management perspective. The SSCM is referred to as an evolving management strategy that aims to achieve equitable conclusions by efficient decision-making based on the use of resources, and less importance has been given to the information technology on-farm (although, many new technologies will aid improved decision-making). The assumption is that better decision-making will provide a wide range of benefits, including economic, environmental, and social, that may or may not be known or measurable during the present. The decisions can be in regard to changes across a field at a certain time in the season or changes through a season or seasons.

To further expand this concept, SSCM can be considered as the application of information technologies that are combined together with production experience in order to:

1. Optimize production efficiency
2. Optimize quality
3. Minimize environmental impact
4. Minimize risk

The functions mentioned above are all at the site-specific level.

This is not a particularly novel concept in agriculture, as there exist essays on this topic dating from the early 18th century. In this case, what is new is the scale at which we are able to implement these aims. Prior to the industrial revolution, agriculture was generally conducted on small fields with farmers often having a detailed knowledge of their production system without actually quantifying the variability. The movement toward mechanical agriculture and the profit margin squeeze has resulted in the latter half of the 20th century being dominated by large-scale uniform “average” agricultural practices. The advancements of technology during the late 20th and early 21st centuries have allowed agriculture to return toward site-specific agriculture while retaining the economies of scale associated with “large” operations.

1.7 VARIABLE RATE APPLICATION (VRA) AND VARIABLE RATE TECHNOLOGY (VRT)

Variable Rate Application (VRA) is the process of the application of inputs at a fluctuating rate, and the mixture of inputs is also changing in order to meet the site-specific requirements – both spatial and temporal – across the field.

There are two basic technologies for VRA, as discussed below:

a. Map-Based VRA:
   A map-based VRA configures the application rate based on information from an electronic map, which is also referred to as a “prescription map.” Using the field position from a GPS receiver and a prescription map of the target rate, the concentration of input is modified as the applicator moves

FIGURE 1.4 Map-Based VRA

FIGURE 1.5 Sensor-Based VRA

through the field. Canopy management can be conducted with a combination of crop sensors and real-time modeling.

b. Sensor-Based VRA (No GPS):

A sensor-based VRA requires no map or positioning system. Sensors on the applicator measure soil properties or crop characteristics "on the go." Based on this continuous stream of information, a control system calculates the input needs of the soil or plants and transfers the information to a controller which, in turn, delivers the input to the location measured by the sensor.

In some SSCM systems, both types of VRA are compatible so as to take advantage of the benefits present in both methods [8].

Variable Rate Technology (VRT) helps in achieving the fundamental objective of precision farming by enabling the optimum application of water, nutrients, chemicals, etc. on the basis of varying site-specific needs. VRT finds their applications in many farming practices so as to apply inputs at a rate that depends on the soil type noted in a soil map that has been generated from GIS. The data that is acquired from the GIS can be extrapolated to find valuable information that can help in control processes – such as seeding, fertilizer and pesticide application, herbicide selection, and application at a variable rate in the right place at the right time. VRT consists of machines and systems for applying the desired rate of crop production materials at a specific location [8].

Variable Rate Technology consists of farm field equipment with the ability to precisely control the rate of application of crop inputs that can be varied in their administration commonly include tillage, fertilizer, weed control, insect control, plant population, and irrigation [17].

In VRT, the system is fitted with rate controllers with the purpose of regulating the application of input that can be of any form – liquid or granular. These rate controllers can monitor the speed of the machine that they are installed on. Therefore, the flow rate and pressure (in the case of liquid inputs) of the material is adjusted in real-time accordingly. Rate controllers are often used as stand-alone systems [12].

1.8 ADOPTION OF SMART PRECISION AGRICULTURE

After previously studying the introductory details about precision agriculture – the concept and the technologies associated with PA – users should also know about another relevant term that is currently popular and one of the most trending topics: “Smart Precision Agriculture.” Industry 4.0 has universalized disruptive technologies like the Internet of Things, artificial intelligence, machine learning, deep learning, cloud computing, Edge-Fog Computing, among other things, that have made drastic changes in agriculture and possess a high potential to make a positive impact on productivity and the profitability of the agricultural sector. Cyber-physical systems (CPS) introduced in agriculture have been one of the causes for its automation. The term “Smart Precision Agriculture” is the result of Agriculture 4.0 (as explained further in Chapter Eight). The increasing demands of the agriculture sector were counterbalanced in Agriculture 4.0 by reinforcing agricultural systems with WSN, IoT, AI systems, etc. Therefore, it accelerated the journey towards smart precision agriculture. Age-old limitations and issues in agriculture were solved because scientific approaches became more efficient and accessible. Smart PA has been able to provide for economic farming, an upsurge in yields and productivity, effective management, etc. All of this has been achieved with the fulfillment of IoT and ML (machine learning) in agricultural practices [22], [23].

Some examples of Smart PA include the following items:

Smart monitoring systems for crops, weather, field, irrigation, soil health, etc. [3], [23–26],
Smart agricultural machinery [4], [23],
Solar-powered automated drip irrigation system [27],
Smart agricultural drones [18], [22],
SMART greenhouse production [22], [23].

The benefits of smart PA are plentiful, and it is not possible to mention every single one in this section.

Rather, some major benefits of Smart PA include:

- Less environmental degradation
- Improvement in production and productivity of crops
- Overall reduction in production cost
- Precise and accurate knowledge about all of the sectors of agriculture
- Minor human intervention
- Adaptive technologies in providing the best results
- Improvement of agricultural practices beyond human limitations using technologies like ML and deep learning
- Excellent management and predictions

1.8.1 Scope of the Adoption of Precision Agriculture in India

“Soft” PA is based on the visual observation of crops and soil and management decisions that are derived from experience and intuition and without proper statistical and scientific analysis. Whereas, “Hard” PA uses all of the modern

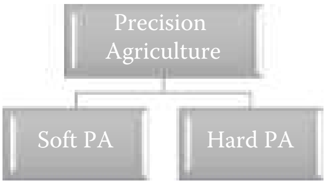

FIGURE 1.6 Types of PA

technologies such as GPS, GIS, VRT, and more that were previously discussed above.

The success of PA in India will be attributed to the balanced use of both "soft" PA and "hard" PA. In India, the land is fragmented, and this becomes the major hindrance for large-scale agricultural mechanization. For centuries, farmers have been practicing types of "soft" PA technology – whether intentionally or otherwise – due to the family responsibility system. Currently, India is producing more than 200 metric tons of food grain; however, the quantity is still insufficient in meeting the demands of the global agricultural market. This proves that quality is necessary to compete with international standards, so here lies the tremendous scope for PA in India.

An example further illustrates this below:

The overall fertilizer consumption rate in India is lower by approximately 2 to 5 times when compared to countries like China, Egypt, and the Netherlands. Studies have shown that, in most of the states of India, if systematic soil testing is done and proper NPK fertilizers are applied, then the productivity level can increase by 2 to 3 times.

However, inadequate fertilizer application still prevails due to costly traditional soil sampling.

- **Scope:** Cheap dynamic soil sampling technology and nutrient status analysis on a large scale by Remote Sensing (RS) and Geographical Information System (GIS) in these states can do wonders.

In contrast, some states – such as Punjab and Haryana – have scale mechanization along with high doses of fertilizers and pesticides which exploit the land

TABLE 1.1
Production Rank and Productivity Rank of Wheat and Cotton in India

Crop Type	Production Rank (Global)	Productivity Rank (Global)
Wheat	2	**32**
Cotton	4	**118**

and excessive use of agricultural input are typical problems. The signs of a depletion in the natural resources deem it more or less suitable for "hard" PA.

1.8.2 Strategy for the Adoption of Precision Agriculture in India

The design of the adoption strategies will affect the application and success of PA in India. Planning must be done by conducting a significant number of experiments and analyses before the administering of PA to Indian agriculture.

There are three steps that must be undertaken in order to enter the Precision Agricultural Age, namely:

1. **Present stage:** This is the initial stage which involves making the public aware of the PA concept through media, workshops, seminars, and other relevant channels. This involves the development of satisfactorily skilled and specialist manpower, proper institutions for PA, and uniform crop and soil management. communication, seminars, workshops, etc.
2. **Intermediate stage:** This follows a layered random sampling within the zone that precisely describes the management zone throughout the country and validates computer models with zone-specific data.
3. **Future stage:** In this stage, zone-specific computer models are simulated for agricultural input conditions and specific sensing and management that involves fine grid sampling and sensing.

Table 1.2 displays a primitive way of making people understand the application of PA below [5].

1.9 SOME MISCONCEPTIONS ABOUT PRECISION AGRICULTURE

Until such time that the PA concept becomes more widely accepted, there will still be certain misconceptions regarding it. A few of these may include the following:

1. Sometimes, PA is misunderstood as yield mapping. In actuality, yield mapping is simply a tool that comes in handy for implementing an SSCM strategy of PA.

TABLE 1.2
The Problem and Its Likely Solutions in Precision Agriculture

Crop Type	Production Rank (Global)	Productivity Rank (Global)
Wheat	2	**32**
Cotton	4	**118**

2. Other times, PA is considered sustainable agriculture – which is not completely true. PA is merely a way to help make agriculture more viable. The development of SSCM as a form of PA was only due to the fact that it had the capability of improving productivity and profitability.
3. Often, PA is misinterpreted with SSCM in the environmental domain. PA has become a tool for environmental auditing of production systems, but environmental auditing does not equate to environmental management. For this purpose, a large amount of fine-scale data is acquired by the SSCM system, which can be used for on-farm environmental risk assessment and incorporated into a whole-farm plan to help endurance in the long term.
4. Machinery guidance and autosteer systems are examples of tools used in SSCM and, therefore, cannot be considered as PA.
5. PA is quite related to cropping, but it can also be associated with any agricultural production system (e.g. animal industries, fisheries, and forestry) in which we actually use the PA without explicitly identifying it [28].

1.9.1 Hurdles Faced by Farmers in Adopting Precision Agriculture in India

There are a number of reasons why there is still a hindrance in the adoption of PA [29]:

1. The high illiteracy rate among Indian farmers makes it difficult for them to adopt PA technologies.
2. The advanced technologies used in PA are a barrier itself due to the fact that these are handled by the aforementioned farmers.
3. Adequate decision support tools are lacking.
4. The proper understanding of the agronomic factors is missing.
5. There exists an inability to streamline information from different sources that have different impact factors.

1.9.2 Present Status of PA in India

Presently, PA is at the infancy stage in India. Many discrete measures have been taken toward its adoption and implementation. Some of these are specified below:

1. A budget of US$285 million has been announced for the **National Agricultural Innovation Project (NAIP), and this is purely dedicated to** PA research.
2. **The** "**Tamil Nadu Precision Farming Project**" has been initiated by the Tamil Nadu Government. Currently, it is implemented in two districts with a future extension to six more. Mainly, it is focused on hybrid tomatoes, capsicum, baby corn, white onion, cabbage, and cauliflower which fall under the category of high-value crops.

3. Bhopal also started variable rate input application in different cropping systems with the joint collaboration of the **Project Directorate for Cropping Systems Research (PDCSR** Uttar Pradesh) and the **Central Institute of Agricultural Engineering (CIAE).**
4. Ahmedabad has admitted experiments with the **Space Application Center (ISRO)** in the **Central Potato Research Station** farm at Jalandhar, Punjab, to make comprehensive studies on the role of remote sensing in mapping the variability with respect to space and time.
5. 17 **Precision Farming Development Centers (PFDCs)** are located in different places in the country to meet the corresponding regional requirements in the fulfillment of PA. Therefore, the development of specialized centers and scientific data bank is considerably important for PA.

1.9.2.1 Some Important Functions of PFDCs are Mentioned below:

a. To popularize and make the public aware of PA
b. To provide training to an extensive number of farmers so that they are able to operate the latest PA technology in order to increase their production
c. To focus on precision irrigation water management, as is the main role of PFDCs

1. The government and private agencies are working as an alliance to elevate PA to greater heights in India.
   An example includes the establishment of a new precision farming center by MS Swaminathan Research Foundation (MSSRF) – a non-profit trust – at Kannivadi in Tamil Nadu with financial aid from the **National Bank for Agriculture and Rural Development (NABARD)** and the **Arava R&D Center of Israel**. The major aim of this precision farming center is poverty alleviation by adopting PA technologies.
2. The strategy for exploring the potential of advanced technology in the agricultural domain by Tata Chemicals Ltd. – a private sector – has been started with a project that aims to:

a. Provide farmers with infrastructure support
b. Arrange for operational assistance in the fields
c. Implement coordination and control of farming activities and strategic support

3. Indian Tobacco Companies (ITC) have established bout 1,200 “E-Choupals” in four Indian states – which are village internet kiosks that provide access to information on the weather, market prices and scientific farm practices, crop disease forecasting system, and expert crop advice system.

It is fairly visible that PA has yet to gain popularity in small Indian farms. Some of the above-stated works have proven rather beneficial to PA in India, whether directly or indirectly, by setting a platform and solid foundation for its adoption at a high scale.

However, no “hard” PA technologies have been adopted to date (Mondal, 2009).

Few soft PA techniques are used on the basis of knowledge gained through experience by the Indian farmers, and this has been the case for centuries. Some initiatives have been taken in providing need-based nutrient applications for paddies, while the use of technology has been initiated at some places.

In order to avail of the complete benefits of precision agriculture, the Indian government should organize and plan certain long-term policies that are not only required for the present scenario, but also have future scope [30].

1.9.3 Status of Precision Farming in Some Developing Countries

The status of countries is different depending upon its limitation and critical parameters of sustainable agricultural development. Alteration in the socio-economic factors of some developing countries is creating new scopes for PA. The world’s urban population has increased ten times during the 20th century, and most of which is associated with low and middle-income nations such as India. Other examples of developing countries that have recently adopted certain PA components are Argentina, Brazil, China, India, and Malaysia. Other countries have started PA on some research farms, but generally, the percentage of adoption is still rather limited. Keeping an eye constantly open for the present status of technology will help in identifying the adoption ways and will also try to concentrate the research in a particular direction. Therefore, there is a need to gain a thorough review of the status of PA in developing countries [30].

Table 1.3 shows the common PA adoption strategies for developing countries by P. Mondal and M. Basu below [30]:

TABLE 1.3
Common PA Adoption Strategies for Developing Countries

Strategic PA AdoptionComponent	Technologies	Target Sectors
Single PA Technology	Single low-level PA technologies, leaf color chart (LCC), small machine-based VRT, etc.	Small-scale farms
PA Technology Package	Soil plant analysis development, LCC, DSS, GIS, VRT, GPS, etc.	Consolidated plots, plantation crops, cash crops, cooperative farming, etc.
Integrated PA Techniques Online	Online sensor, image processing, RS, yield monitoring system, VRT, GPS, etc.	Organized farming sector

1.10 CONCLUSION

The introduction of PA has marked the beginning of a revolutionary era in agriculture that is tech-powered and has made use of technologies to avail of maximum benefits. PA focuses on the site-specific variabilities within the field in order to address all concerns precisely. The technologies like GIS, GPS, satellites, RS systems, sensors, etc. have been widely used to achieve the aims of PA. Production, productivity, and profitability have upgraded in comparison to traditional agriculture. Moreover, better management has been achieved through PA. Thus, in simpler words, PA uses information and technologies for accomplishing effective management strategies. It is important to understand that PA is a procedure that causes agriculture to become more sustainable, and SSCM is only a form of PA. In summary, PA is completely about the optimizations of the inputs in order to attain a maximum outcome, as per the variation across the field.

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2 Smart Intelligent Precision Agriculture

2.1 MODERN DAY AGRICULTURE

The world population is increasing at an accelerated rate, thus making it a concern to feed such a considerable population. According to a UN report, the world population is expected to reach approximately 8.5 billion in 2030 [1]. This has made agriculture a rather important area to focus on.

Modern-day agriculture not only aims to feed, but also to nourish even with limited resources available. Beginning from the era of handheld tools to the age of AI-powered machines – specifically, intuition-based agriculture to today's data supported decision systems – agriculture has undergone remarkable changes. The aim of every modification has always been to improve agriculture so it can fulfill the requirements of society. Modern-day agriculture is surrounded by a hyper-digital environment that introduces impact on it as well. The state of art technologies – such as artificial intelligence, IoT, big data, etc. – are being termed as "disruptive technologies" due to the fact that these are transforming and revolutionizing the entire world, and agriculture is no different. Agriculture has undergone a series of changes that have either caused significant alterations or complete transformations in its various sectors. Major modifications have been witnessed in the past half-century. Modern agriculture is also known as "tech-driven agriculture" and is designed to avail of maximum benefits from the latest technology.

Precision agriculture focuses on the site-specific requirements in a field and data that is derived from the aerial images, sensors, GPS, GIS, etc., and was analyzed to identify the areas and parallel necessary inputs. In this case, instead of applying uniform input throughout, an optimized site-specific application was executed. The variations in the field were found by the PA tools, and corresponding optimizations were provided accordingly [2].

Smart technological innovations have been introduced in agriculture, and these have improved production, productivity, and management. Intelligent agriculture is considered as an agricultural system that utilizes modern technologies like the internet platform, fog/edge computing, cloud computing and storage, state-of-the-art "information and communication technology (ICT)," intelligent machines, and intellectualization of agricultural management with special attention to the environment. This has resulted in the development of "smart farming." It includes all of the components of PA and enables managing production processes. Intelligent agriculture is an important step toward sustainable agriculture [3].

In "smart agriculture," the primary focus is data and the application of data. Optimized, complex systems are formed to use the gathered data in a smarter way. Smart agriculture is centralized on the efficient decisions that are highlighted and leveraged with the use of technologies like big data, GPS, GIS, drones, cloud computing and storage, edge/fog computing, IoT, etc. [2]. It is distinct from PA in the sense that it is not merely based on location information [4]. It is focalized on data and situation awareness, as triggered by real-time events [5].

Big data provides predictive insights for the outcomes in order to drive real-time operational decisions and other related processes. Big data applications have changed many of the approaches in traditional agriculture. However, it is rather difficult to say if the algorithms in the future can possibly replace farmer knowledge [6].

Currently, autonomous, robotic, and unmanned aerial vehicles have been developed for farming purposes [7], [8] – such as mechanical weeding, application of fertilizer, or harvesting of fruits; when equipped with hyperspectral cameras, these devices can also be used to calculate biomass development and fertilization status of crops [9], [10].

2.2 DIGITIZATION OF AGRICULTURE – DIGITAL FARMING

The digitization of agriculture refers to the evolution of agriculture from "precision agriculture" to significantly more advanced, centralized, and knowledge-based production systems. In simpler words, digital farming is an upgrade to precision farming (PF). The tools and techniques that are used in digital farming include those present precision farming with the addition of intelligent networks and data management tools. Digital farming covers *all* of the aspects of agriculture [11]

Digital farming has a broader aim of utilizing all of the available information and experiences in order to conduct automation in the various processes of PF [11]. It mainly centers on the "value of the data" so as to derive certain actionable insights in order to further develop precision farming. Some of the experts state that digital farming is a combination of precision farming and smart farming [12].

The invention of new and improved devices – such as sensors, actuators, and microprocessors, etc. – and the advancements in communication standards, cloud-based ICT systems, and development in data sciences resulted in the employment of data that was being generated into valuable actions. Data management is of fundamental importance in digital farming, because high volumes of data that are obtained must be handled in a manner wherein retrieving values specifically collected from this data should be possible. Transferring data management to a data portal makes it easier to control the processing and flow of information. Digital farming allows the user/farmer to decide the allocation of access rights so, in this aspect, the user can retain "ownership" of the data. Further upgrades are limited in the case of the technological hardware when compared to the possibilities of improvement offered by the data algorithms.

Digital farming is anticipated to make maximum extraction of values from the data:

- **Data as a technology enabler:** Digital farming enhances other precision farming tools by incorporating new and improved data algorithms that are significantly more accurate.
- **Refined production processes: Connected devices, a partially automated collection, and the** targeted analysis of data help in upgrading the production process.
- **Decision support:** Data that is obtained from multiple sources is fed to a system that processes and interprets the aforementioned data to support the farmer in decision-making.
- **Optimization of farm operations, inputs, and outputs:** Data is used to reinforce the performance of the operations carried out, inputs applied, and the output gained using additional services.

Digital farming already is a reality in some areas: For instance, there exist GPS guidance systems for controlled traffic farming, site-specific fertilization, or plant protection measures as part of a complete production/input cycle using proprietary cloud-based connectivity. This being said, automated data processing and completely integrated, harmonized networks are still a not-so-distant future for agriculture and agricultural machinery. Dedicated efforts from all concerned actors are necessary to realize this future vision. Manufacturers of agricultural machines should focus, first of all, on the development of highly efficient and sophisticated machines that are suitable for digital farming. In other words, the industry should direct their attention to the advancement of machines that are compatible with the digital infrastructure of the farm and can make the required contribution to the optimization of production processes.

Digitally smart machinery should possess the following features:

- Ability to transfer data (i.e. send or receive data)
- Capacity to perform the functions with the least human intervention
- Enabling optimal utilization of machinery
- Intelligence to guide the user

2.3 TRANSITION TO SMART INTELLIGENT PRECISION AGRICULTURE

The first breakthrough in agriculture was the invention of handmade tools – such as hoes, sickles, and pitchforks – that were used for cultivation. These were used until the end of the 19th century; accordingly, this era is known as Agriculture 1.0 [14]. This time was characterized by low productivity and was entirely based on manual labor.

With the onset of the First Industrial Revolution or Industry 1.0 during the period between 1784 and around 1870, there was a significant increase in

FIGURE 2.1 The Development Roadmap of Industrial Revolutions and Agricultural Revolutions [13].

agricultural production, herein referred to as Agriculture 2.0. Machines that were used in various agricultural practices notably increased food production while reducing manual labor.

The Second Industrial Revolution (2IR) occurred in the 20th century and is also known as Industry 2.0. New sources of energy were discovered and used in machines – specifically, oil and gas. Transportation improved as a result and caused the development of the agri-food supply chain. At this point, agricultural products were shipped to longer distances; thus, previously isolated communities became connected with the rest of the world.

Industry 3.0 resulted in the advancement of embedded systems, software engineering, and communication technologies. The concept of renewable sources came into existence, people started looking at these sources like photovoltaic power, hydroelectricity, and wind power. All this induced an agricultural revolution, which is known as Agriculture 3.0. Precision agriculture is one of the important transitions in agriculture, which was supported by Industry 3.0 in terms of yield monitoring, variable rate applications, and guidance farming systems. In general, these industrial revolutions caused the transformation of "undefined labor-intensive agriculture" into "industrial agriculture" [10].

4IR is still ongoing, and it has made an important fusion of emerging technologies such as the Internet of Things (IoT), robotics, big data, artificial intelligence (AI), and blockchain technology. Thus, giving rise to autonomous and intelligent machines that aid industrial production processes and supply chains. Hence, this induced another agricultural revolution which was referred to as Agriculture 4.0 [15].

Its key attributes are real-time farm management, a high degree of automation, and data-driven intelligent decision-making, agri-food supply chain efficiency, and food [13], [16].

Agriculture 4.0 will be further explained in the chapter, "Agriculture 4.0 – The Future."

2.4 BENEFITS OF SMART INTELLIGENT PRECISION AGRICULTURE

The benefits of the smart intelligent precision agriculture will be further examined in the succeeding chapters of this book in context with specific technology. In this section, a general overview of the advantages will be provided. Certain assets of smart intelligent PA are mentioned below:

2.4.1 Effective Crop Management

Crop management is a critical task when it comes to increasing the production and quality of the crops. For this purpose, historical data plays a key role in crop management. Precision agriculture requires insight that is acquired from a deeper analysis of the data so that every action bears maximum efficiency. Some of these examples include water quantity required, time of watering, amount and time of fertilizer and pesticides application, etc. Under a sophisticated IoT-based management technique, real-time information reaches the farmer via email or SMS – whatever is convenient. This has unfolded the next stages in crop management.

The introduction of AI and ML in the agricultural practices for crop monitoring has a profound and positive impact on agriculture in general, as many of its aspects have been enhanced. AI in crop sowing is used essentially to drive predictive analytics to determine the best time and method in sowing. Furthermore, crops can also be planted using AI-aided machinery at equidistant intervals and at optimal depths. The selection of a proper type of crop plays a fundamental role in determining the yield, and this choice depends on various parameters such as the topography of the region, climate, soil type, composition of the soil, market trends, etc. AI and ML help in finding new possibilities to improve every step taken in agriculture. Moreover, this is also paving way for further developing crop quality. Human limitations in analyzing data and forming relations among various relevant parameters are examples; on the other hand, an AI-powered machine can use this information to recommend a method that can enhance crop quality [17].

2.4.2 Excellent Soil Management

Thorough and complete knowledge about soil is necessary to boost agricultural yield; therefore, the available information about soil must be accurate in order to acquire acceptable soil management. The data of agricultural soil properties – such as the estimation of soil drying, condition, temperature, and moisture content, etc – are administered to an ML model that serves as a reliable solution in providing valuable insights. Hence, availing of the maximum benefits of soil management becomes more convenient for agricultural purposes [18].

Specific examples of the abovementioned technology include Trace Genomics – Machine Learning for Diagnosing Soil Defects, which is similar to the Plantix application [19]. California-based Trace Genomics provides furnishes farmers with soil analysis services. Its lead investor, Illumina, helped develop the system which uses machine learning in providing clients with information about their soil's strengths and weaknesses. After submitting a sample of soil to Trace Genomics, users reportedly receive an in-depth summary of their soil contents [20].

2.4.2.1 Easy Remote Monitoring the Farm

The agricultural industry provides a large number of options in terms of farm management. Some of these include cattle farms, poultry farms, beehives, etc. IoT has revolutionized these fields altogether, causing both direct and indirect types of impact on agriculture.

With the establishment of IoT in agriculture, there has been a lot of improvement in this sector. People have discovered certain brilliant and innovative ideas. An example of such an idea was preventing the attack of animals in the fields. Known conventional methods were not adequate, so IoT and cloud-based technology were used and this significantly reduced the loss of lives in this specific case [e-Device for the Protection of Agricultural Land from Elephant Attacks in Odisha: A Review] [21].

2.4.3 Smart Intelligent Irrigation System and Water Quality Management

A smart irrigation system is an essential need for agriculture. For this purpose, soil moisture content and temperature data are regularly determined by sensors and is passed to a processing unit or can sometimes be interpreted by the sensor itself. With the help of the same IoT system, water quality monitoring can also be done in real-time. All of these factors contribute to making irrigation and water quality management fundamentally easier. Also, the AI-powered smart automated irrigation systems are capable of continuously providing precise and optimal irrigation that is necessary for maintaining desired soil conditions. This reduces water wastage, labor costs, production costs, and, at the same time, increases overall yield. Many scientists believe that judicious use of water in these irrigation systems is likely to have a positive global impact on water [17]. The estimation of evapotranspiration is necessary to design and manage a smart irrigation system, but it proves to be a complex process to accurately calculate. This problem is solved by AI and ML algorithms that are able to precisely estimate evapotranspiration [18]. Specific examples include Cultyvate [22] and DIGITEUM [23], among others.

2.4.4 Intelligent Agricultural Robots

Intelligent agricultural robots are some of the rather successful intelligent machines used in this type of agriculture. The agriculture realm is possibly one of the most important fields in the world that have been provided with automation and smart devices that can perform functions that once traditionally needed human intervention. Companies are developing and programming autonomous robots that are capable of handling essential agricultural tasks – such as harvesting a higher volume of crops at a faster pace compared to human laborers who are using this disruptive technology. An example of this is RIPPA, a robot that exterminates pests and weeds [24].

2.4.5 High Accuracy in Disease Prediction, Detection, and Control

Each year, there is approximately a 37% loss in crop production. Predictions are done based on computational analysis. Both machine learning and deep learning are incorporated, and diseases and pest attacks can be forecasted using various algorithms. Convolutional neural networks are also used to train the system. IoT has the unique feature of being able to inform the farmer via a cellular network using his/her phone so they can take necessary action.

Accurate disease prediction is a breakthrough in smart intelligent precision agriculture. Early disease detection and even disease prediction have promoted better-quality yields. Accurate detection is made possible by AI and ML techniques. AI and ML models have successfully been able to analyze heterogeneous data and data with a lot of noise more advantageously [25–27].

2.4.6 Labor Challenge Mitigated

The shortage of laborers has reportedly led to millions of dollars in revenue losses in key farming regions. Machines that are currently used in smart intelligent precision agriculture have made it possible to compensate for the reduction in available manpower for agricultural practices. Examples of such efforts include Harvest CROO Robotics, notably for crop harvesting.

2.4.7 Leads Way from Precision Agriculture to Agriculture 5.0

Another use of smart intelligent precision agriculture is that with the adoption of all of the components of PA in combination with smart and intelligent agriculture technologies like WSN, IoT, AI, ML, big data analytics, blockchain, etc., smart intelligent precision agriculture has paved way for the paradigm shift from “precision agriculture to “Agriculture 5.0.” In some particular tasks, these smart machines that are powered by AI are able to outperform a human expert. Such examples include the use of computer vision in image analysis [17].

2.4.8 Smart Intelligent Greenhouse

With IoT in action, greenhouse shortcomings have been significantly mitigated. The WSN that can be deployed in greenhouses can oversee environmental conditions and transmit this specific data to a storage location, after which the data is analyzed using an array of sophisticated tools and diagnostic models. Monitoring becomes easy; remote access to various elements like the irrigation system, light intensity system, temperature control system, etc is now possible. In modern times, a farmer can manage a number of processes through a smartphone [5]. AI has a crucial application in a greenhouse for scrutinizing functions. The AI-backed system is designed to control and manage the climate of the greenhouse with an emphasis on rigorous analysis of data in order to achieve a high level of precision. Due to various parameters that must be considered while adjusting the climate of the greenhouse, it becomes a tedious task to handle through conventional means. Artificial Neural Networks (ANNs) and Fuzzy Logic Controllers (FLCs) are some of the methods used in this process to attain high accuracy in regulating temperature and humidity [17]. These technologies have contributed to transforming the traditional greenhouse into a smart intelligent greenhouse.

All of the benefits mentioned above are implemented with security as the primary concern. Highly secure encryptions are used for devices as well as the data involved in “smart intelligent precision agriculture” [28].

2.5 CONCLUSION

Every industrial revolution has made a powerful impact on agriculture. Moreover, precision agriculture marked the beginning of a new era in agriculture. Concepts like digital farming and smart farming that are sometimes used interchangeably actually have notable differences. Disruptive technologies have transformed agricultural practices and have caused the emergence of a new concept that is known as Agriculture 4.0. Further advancements in technology have brought “smart intelligent precision agriculture” into existence, which is a combination of all of the pioneering technology adopted – such as AI, ML concepts, deep learning concepts, and more – in a smart precision agricultural system with machines that have certain relevant artificial intelligence.

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3 Adoption of Wireless Sensor Network (WSN) in Smart Agriculture

3.1 SENSORS AND WIRELESS SENSOR NETWORK

The concept of automating the collection of physical information by monitoring environments is still in its infancy. Developments in the silicon industry in conjugation with Moore's Law paved a path for the design of rather unique, small, and robust alternatives that were developed and used for the task of monitoring physical entities in the surrounding environment. With the advancements in semi-conductor, networking, and material science technology, the use of electronic instrumentation for the automation of daily life tasks has become a new domain of experimentation and experiences. The design and cost-effectiveness of the three technologies have given birth to a new branch of potent networking hardware devices called sensors.

Sensors, also referred to as motes, are "battery-operated hardware that have the capability of sensing physical information, processing, and communicating information among other sensors or directly to the base station or a remote storage." In other words, a sensor node can be defined as "an electronic device with a limited power supply that is able to produce a measurable stimulus required to modify a physical condition that is being sensed by the node." The sense organs present in a human being are the best metaphors of what a sensor node is and how it functions. Each sensor node has four main components: a micro-controller, a transceiver, a power source, and external memory, as shown in Figure 3.1, and this can either be analog or digital in nature [1–3].

Analog sensors produce raw analog signal (in the form of a continuous waveform) values depending on the physical environment that they are detecting. ADCs are required to convert this wave nature information into digital form (i.e. 0s and 1s), for easier understanding of the micro-controller as well as the human operator.

Digital sensor directly recognizes the data in the form of 0s and 1s – specifically, complete digitization hardware is in place. These employ high power constraints, and every action must be accurately timed.

3.1.1 Power Subsystem

Due to the wireless and computational nature of a sensor node, an adequate power supply is required for the node to be able to function properly. An external

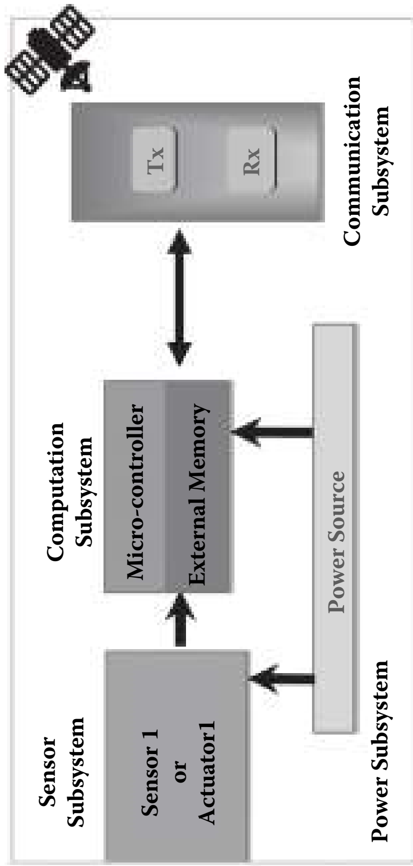

FIGURE 3.1 Typical Architecture of a Sensor Node.

battery or solar power source is attached to a node, as nodes need to be deployed for monitoring and processing of detected information of a particular target under consideration. In this case, the different types of batteries that are used for sensors are either rechargeable or non-rechargeable and are composed of electrochemical elements such as NiCd (Nickel Cadmium) and Lithium-ion, among others. Most of the current research is focused on the development of energy-efficient data transmission and aggregation schemes such as dynamic power management (DPM) and dynamic voltage scaling (DVS), and these are used in order to maximize the use of the rather limited battery power source of nodes [4], [5].

3.1.2 Computation Subsystem

The computation subsystem consists of two important components – namely, a micro-controller and a storage unit. The micro-controller is a small computer placed on a single metal-oxide semiconductor that is an integrated circuit chip with power consumption defined in milliwatts or microwatts. The micro-controller is responsible for processing information as well as computing and controlling the other units of a node – comparable to the CPU of a computer. Each micro-controller has a memory unit along with some programmable input/output features. The attached memory unit is non-volatile flash memory (EEPROM, ROM) which is used to store necessary program instructions or application-related data. Certain famous micro-controllers include Texas Instruments MSP 430, Atmel Atmega, and Intel StrongARM [2], [6].

3.1.3 Communication Subsystem

The communication subsystem consists of the module that is in charge of the communication aspect of the sensor node that is used for the transmission of

FIGURE 3.2 8051 Micro-Controller [7].

collected information. Wireless forms of communication – such as radio frequency (RF) or infrared – are notably common forms for sensors. Together, the transmitter (Tx) and receiver (Rx) comprise the transceiver of the node and are responsible for transmitting and receiving radio signals for possible communication.

3.1.4 Sensor Subsystem

The sensor subsystem is a piece of hardware that detects the changes in a specific parameter of a target instance and subsequently forwards the collected information to the micro-controller for processing. Analog to digital converters are used to digitize raw analog data of sensors, thus making this convenient for the micro-controller (μc) to analyze. The accuracy and sensitivity of a sensor are its main features. With the breakthrough in microelectromechanical systems (MEMS), micro-sized sensors bearing the least amount of power and cost are being developed, and a shift towards the design of disposable, easy-to-use sensors is gaining momentum [4].

Combining the collaborative power of different function types of wireless sensors in order to monitor large target areas has gained popularity during the last three decades, and this has grown to be known as wireless sensor networks or sensor web. Wireless sensor networks (WSNs) are defined as, "a network of sensor nodes that are scattered over a region of interest to sense and collect physical, chemical, or biological data patterns that are either spatial or temporal in nature and transmits the data to a central station over a communication link through the network gateway" [1–3]. A WSN is formed by numerous secondary or primary mobile or stationary sensor nodes that are distributed spatially, sometimes even left unattended, and laid out in a predefined topological form (e.g. mesh or star) to collect designated information and transfer this to a remote central storage server for necessary and meaningful end action. Today, state-of-art WSNs require less maintenance, deployment constraints, and costs. Currently, the WSN domain has motivated a significant amount of growth and support in building a number of application-specific software and hardware with minimal energy consumption but with routing algorithms, system security, and reliability.

Due to overwhelming characteristics, sensor networks have found their way into diverse applications ranging from home, workplaces, environment, defense, advanced Industry 4.0, disaster management, intelligent transportation system, Agriculture 5.0, and beyond [1], [8].

Depending on the nature of WSN deployment, the sensor network can fall under the following types [9]:

- **Terrestrial WSNs:** a collection of thousands of wireless sensor nodes that are placed over the ground in either a planned or random fashion in order to monitor the area

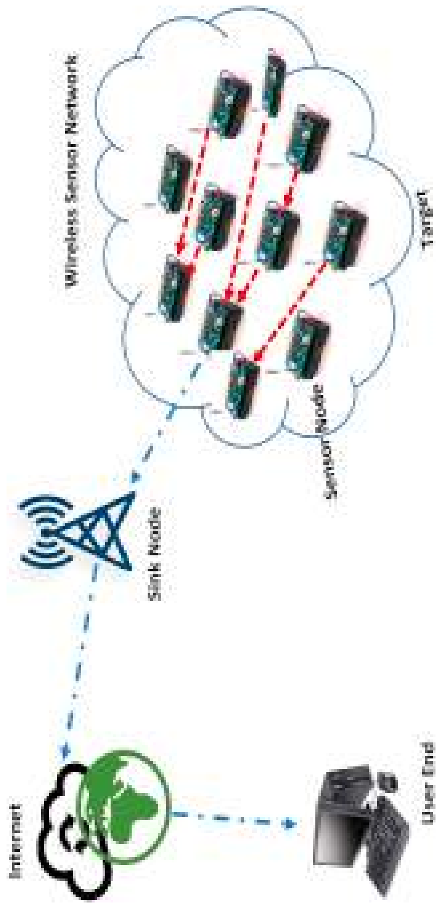

FIGURE 3.3 Overview of a Wireless Sensor Network [8].

- **Underground WSNs:** a type of network in which sensor nodes are buried deep inside the ground to collect information, which usually becomes costly as additional sensors are used to act as mediators on the ground for the transfer of information
- **Underwater WSNs:** a network type where many water-resistant sensors are placed inside bodies of water and use high energy management, data transfer schemas, and protocols.

3.1.5 Multimedia WSNs

Multimedia WSNs are a type of network that is used where wherein the data that is required to be detected is of image, sound, or video nature. A number of camera or sound sensors are set up over the region of interest in order to capture required information.

3.1.6 Mobile WSNs

Mobile WSNs are a type of network that is the most versatile and dynamic in nature. These use sensors to detect motion in order to monitor objects that are in action on a real-time basis.

3.2 EVOLUTION OF WIRELESS SENSOR NETWORKS

The birth of WSN dates back to the Cold War era. The sound surveillance system (SOSUS), which was developed by the US Military in the 1950s, was used to keep watch on the presence of Soviet Submarines. This was an underwater type of network which possessed a hydrophone and an acoustic sensor that is placed inside the Pacific and the Atlantic Ocean. SOSUS is still used by the National Oceanographic and Atmospheric Administration (NOAA) for marine monitoring. In the 1980s, the conception of Distributed Sensor Networks (DSN) by the Defense Advanced Research Projects Agency (DARPA) started to make progress. Due to the success of this project, academic institutions like the Massachusetts Institute of Technology (MIT) and the Carnegie Mellon University were tempted to make WSN popular within the civilian and educational domain. In the 1990s, an initiative was spearheaded by the University of California, Berkley with the blessing of Smart Dust, attained success in the development of the compact and affordable MEMS sensor. In the 21st century, the DARPA-backed project – namely, SensIT – provided an effort to further enhance the capabilities of old bulky nodes. Several industrial and academic initiatives were taken up to strengthen the introduction of WSN in every day-to-day task – for example, the Center for Embedded Network sensing (2002), Zigbee Alliance (2002), NASA Sensor Webs (2001), among others. Today, an era of powerful versatile nodes has evolved with a drastic decrease in size and cost but with a corresponding increase in performance and availability [11], [12].

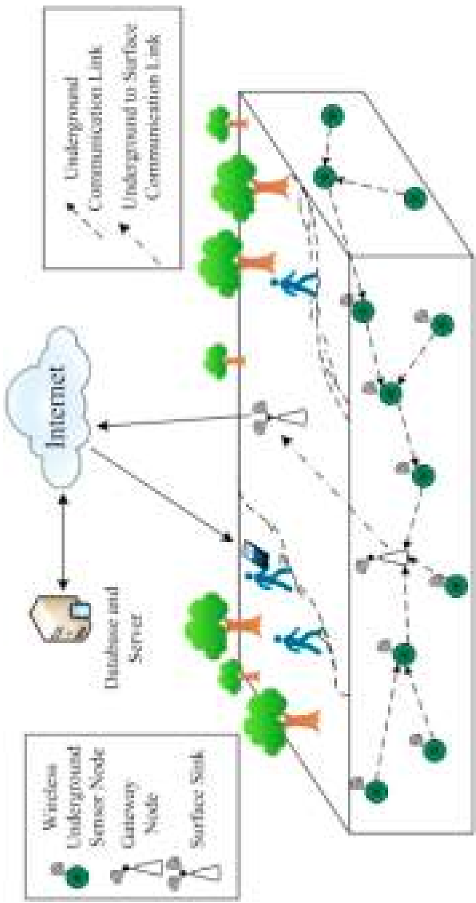

FIGURE 3.4 Overview of an Underground Wireless Sensor Node [8], [9].

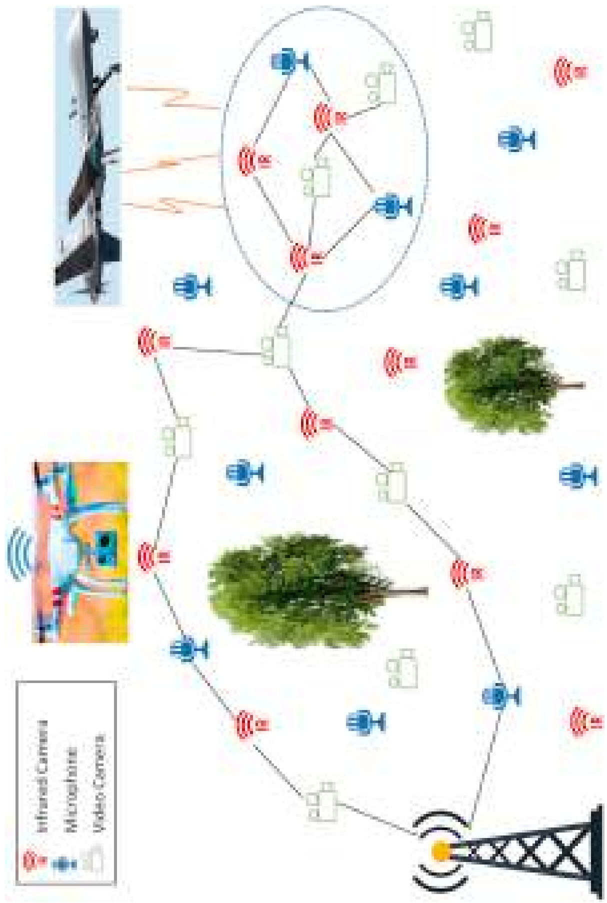

FIGURE 3.5 Overview of a Multimedia Wireless Sensor Network [8], [10].

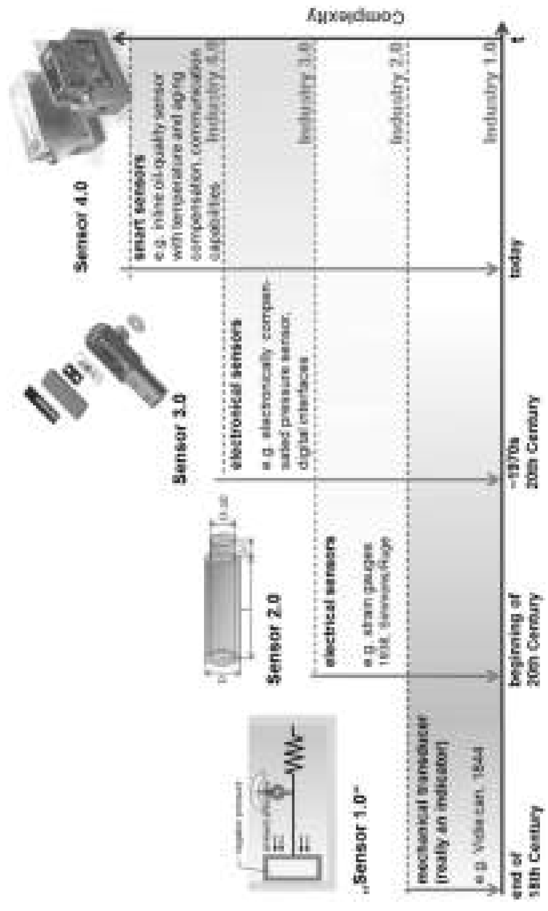

FIGURE 3.6 Evolution from a Traditional Sensor to a Smart Sensor [13].

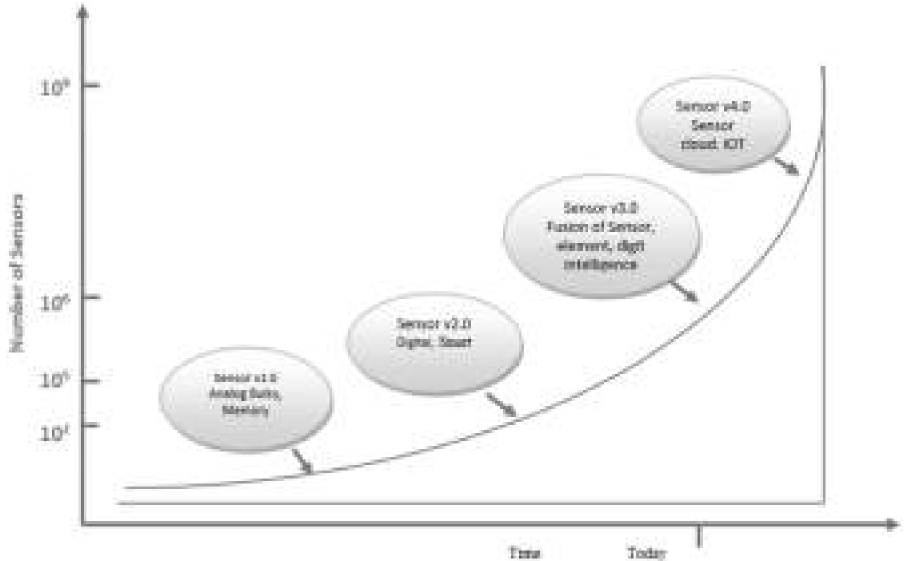

FIGURE 3.7 Generations of Sensors, from Passive toward Smart Sensors [14].

3.3 INTRODUCTION OF WSN IN AGRICULTURE

Agricultural practices have constantly been evolving since the First Agricultural Revolution. The birth of variable rate application technology in the traditional agricultural setup and the use of GIS- or GPS-based tools truly paved the path for precision agriculture practices. PA has rapidly flourished worldwide and has slowly started to embrace new technologies that were rather autonomous in nature. In the late 1990s, the inception of sensors in daily life tasks was at its peak, and researchers began to use and benefit from the application of sensors for precision agricultural practices. Many initiatives that were executed before were as [15–19] and many more. Until the end of 2018, the sensor-based agriculture market amounted to US$1.23 billion globally and is expected to rise to US$2.56 billion by 2026, at a Compound Annual Growth Rate (CAGR) of 11.04% [20].

3.4 FEATURES OF AGRICULTURALLY BASED SENSORS

WSN design, deployment approaches, and features for the agricultural sector are not notably different from the general WSN scenario; however, many considerations must be taken into account before making the right decision in terms of technology to use. Some important factors include [20]:

- **Spatial Scale:** What is the size of the field to be monitored (e.g. locally in terms of hectares or square meters and globally in the cases of large regions)?
- **Time Scale:** How long will the area be monitored (e.g. yearly, weekly, or seasonal)?
- **Spatial Variability:** What is the rate of change in the spatial scale of the area under observation (e.g. dense or sparse)?
- **Time Variability:** What is the rate of change in features of the area to be monitored (e.g. slow or fast)?
- **Responsiveness:** What is the nature of the information that is to be provided to the farmer (e.g. real-time or offline)?
- **Accessibility:** How easily accessible is the location?
- **Non-Intrusiveness:** Should the node placement be visible, hidden, or non-interfering with other systems?
- **Deployment and Maintaining Cost:** What is the cost for the maintenance and deployment of the system?

The deployment of a WSN can be random or structured depending on the coverage and connectivity of the nodes of the network. Various techniques, like geometric principles, can be employed in order to compute the distance among the nodes (i.e. the source) and between the source and the central storage sink for optimal placements within a structured network placement; however, this is not the case for random placement fashion. In an agricultural WSN setup, heterogeneous or similar types of nodes can be placed, and these can be mobile in nature or location-aware (e.g. GPS-enabled). Each node senses the required data, either in digital or analog form, and forwards this to a central sink or another node with the help of predefined software or hardware rules over a secure communication channel for interpolation and generation of relevant outputs. Remote users can use the internet to control, monitor, and observe each action based on the inputs from the sensor data. Different sensor application approaches have been introduced in PA and are based on the following requirements: remote sensors, networked info mechanical systems (NIMS), and embedded networked systems (ENS). In a distributed sensing environment, NIMS or remote sensors can support a farmer in dealing with the rather dynamic and unpredictable nature of the farm, and ENS or ground-based sensors are more economical and able to provide site-specific information although not quite versatile [21]. As observed in the general sensor network, agricultural WSN consists of a coordinator (i.e. a sink which governs the entire network), routers (which route information), and end devices (i.e. the source sensor nodes). The design and deployment dimensions for WSN in agriculture are conducted by the following technical characteristics of WSN:

- **Wireless Networking:** WSNs are capable of measuring high variability in terms of both time and space, thus making the information accessible on a real-time basis. Furthermore, the wireless nature reduces installation costs and power consumption.
- **Compact Size**
- **Low Cost**
- **Reliability**
- **Mobility**
- **Security**
- **Low Energy Consumption**
- **Web-based Data Management:** Storage, mining, and processing of gathered data are crucial for the monitoring system. Such extensive and important data can either be saved on the internet or delivered to the farmer. Various other web-based platforms for collecting and displaying geographical data exist – for example, Global Sensor Networks (GSN) and SenseWeb [22], [23].

Research in WSNs is aiming to overcome the above constraints by developing or improving protocols, algorithms, software, and hardware.

3.4.1 Communication Standards and Protocols

In the world today, different wireless technologies and standards are used for Wireless Sensor Networks (WSN) based on specific needs for connectivity – namely, the availability of power (battery-driven or otherwise), local radio frequency regulations, the density of sensors, distance to the sensor, the frequency that sensors need to be read, the amount of data, the infrastructure, and beyond. The use of battery- or solar-operated sensor networks for monitoring vast agricultural fields demands the use of reliable, secure, cost-effective, and low-powered connecting technology for the transmission of data from the source node to sink nodes via a gateway (i.e. a bridge between two networks). WSNs tend to use license-free communication frequencies or Industrial, Scientific, and Medical (ISM) Band frequencies. The IEEE 802.15.4 working group provides a standard for power-constrained device connectivity and commonly sensors use one of these standards for connectivity such as Zigbee, Thread, WirelessHART [24], MiWi, and 6LoWPAN. Other prevalent technologies include WiFi, Bluetooth, General Packet Radio Services (GPRS)/3G/4G, WiMAX, Z-Wave, RuBee, RFID, ANT, laser, infrared, and Wibree.

Zigbee is the most renowned communication standard that is used in agricultural application monitoring. It is simple, affordable, and consumes less power as compared to WiFi and Bluetooth, with a defined rate of 250 kilobits per second and a transmission range of 10–100 meters [25], [26].

3.4.1.1 WiFi

WiFi is an acronym for Wireless Fidelity. It is a trademark of the non-profit WiFi Alliance and family of wireless networking technologies, based on the IEEE 802.11 family of standards, and is commonly used for connecting devices in a local area network (LAN) and internet access. Furthermore, WiFi is another common technology utilized in agricultural sensor devices, especially drones. WiFi uses mostly the 2.4 gigahertz (120 mm) ultra high frequency (UHF) and 5 gigahertz (60 mm) super high frequency (SHF) industrial, scientific and medical band (ISM) radio bands. It has a transmission range of about 20 meters when used indoors, and 100 meters or 490 feet when used outdoors. It can achieve speeds of over 1 gigabit per second (Gbit/s).

3.4.1.2 Bluetooth

Bluetooth is a low-powered and less expensive communication protocol based on the IEEE 802.15.1 standard. It has a coverage of 8–10 meters with a data rate capacity of 1–24 Mbps. The ubiquitous nature of Bluetooth makes it markedly suitable for use in multitier agricultural applications [27].

Bluetooth Low Energy (BLE) was introduced by Nokia in 2006, and **Wibree** also announced Baby Bluetooth [28], but this was later merged with the Bluetooth standard version 4.0. in 2010. It uses the 2.4GHz ISM frequency band [28], [29].

3.4.1.3 GPRS/3G/4G

GPRS is a packet-based wireless communication service for Global System for Mobile (GSM)-based cellular phones. Data rates from 56 up to 114 Kbps for 2G, and this service guarantees internet connection for mobile device and computer users. With the introduction of 3G and 4G, third and fourth generations provide higher data rates of 200 Kbps and 100Mbps to 1Gbps in 3G and 4G respectively.

This allows users to interact with multimedia websites and similar applications in real-time while using available mobile devices and computer systems. This type of technology is not only universal and readily available to every average person, but it also aids in real-time tracking and monitoring of fields and crops. Finally, the Short Messaging Service (SMS) is one of the best features of this technology [24], [30], [31].

3.4.1.4 WiMAX

Worldwide Interoperability for Microwave Access (WiMAX) is a wireless communication standard that is dedicated to the interoperable advancements in the IEEE 802.16 standards family. WiMAX is purported to provide a data rate of 0.4–1Gbps on immobile devices, and the transmission range for this technology is 50 kilometers. It is more energy-efficient compared to 4G Long-Term Evaluation (LTE) and Evolved High-Speed Packet Access (HSPA +). WiMAX, because of its range and speed, is used as a satisfactory replacement for other technologies in crop monitoring systems, real-time examination of remote sensor-operated irrigation, and spray systems [32]. Table 3.1 provides more insight into the characteristics of these available communication technologies.

3.4.2 Specific Hardware Requirements

At the hardware level, new designs are being introduced in order to scavenge energy from the surroundings. For example, solar cells are embedded into nodes to absorb the sun's energy and convert it into electrical energy. Multiple hardware adjustments have been incorporated depending on the working status (e.g. off, active, idle) of each of a node's components so battery power is conserved. Only the specific components that are required to be active at a particular time are on. Besides the basic components of a sensor node, the competition among various sensor platforms has thronged the market, differing in cost, functioning, or ease of use. Interoperability among all of the heterogeneous platforms is not a serious issue following the use of heterogeneous sensors. Platforms like Arduino, Raspberry Pi, TelosB, SunSPOT, LOTUS, IRIS, and MICAz are popular within agricultural research and practice. Further commercial development of hardware for sensors from companies such as Sensirion, Libelium, Decagon, XBee, METER, Intel, and Qualcomm has resulted in highly innovative, multipurpose, diverse coverage areas, and cost-effective sensor designs. Readers can refer to these sources for an extensive study of different types of sensors used in a vast number of agricultural activities [33–36].

Arduino is an exhaustive platform that spans across software and hardware. It is called a breakout board, where sensors or actuators are wired using pins called jumper wires on a breadboard and are programmed using Arduino IDE. It comes with a microprocessor and is, therefore, referred to as a tiny computer. Raspberry Pi is another common Linux-based board that is used to connect several sensor devices under one platform. Such boards can readily be purchased from the market for hands-on work and at the amount of a mere few dollars. In addition,

TABLE 3.1
Characteristics of Various WSN Communication Standards

Parameter	ZigBee	WiFi	Bluetooth	GPRS/3G/4G	WiMAX	Wibree
Standard	IEEE 802.15.4	IEEE802.11a,b,g,n	IEEE802.15.1	-	IEEE 802.16 a,e	IEEE802.15.1
Frequency Band	868/915MHz,2.4GHz	2.4GHz	2.4GHz	865MHz, 2.4GHz	2–11GHz (mobile)66GHz (stationary)	2.4 GHz
Data Rate	20–250 kbps	2–54Mbps	1–24Mbps	50–100 kbps/ 200kbps/ 0.1–1Gbps	Up to 100 Mbps(stationary), Up to 50mbps (mobile)	1 Mbps
Transmission Range	10–20m	20–100m	8–10m	Whole GSMnetwork	≤ 50km (stationary)<= 15km (mobile)	5 to 10 m
Energy Consumption	Low	High	Medium	Medium	Medium	Low
Cost	Low	High	Low	Medium	High	Low

the NodeMCU is board-based on the ESP8266 micro-controller. This board comes with WiFi and is budget-friendly and is freely available on Amazon and eBay. This WiFi-enabled board helps in developing and testing projects as well as sending data over WiFi to a cloud or other storage servers.

3.4.3 Specific Software Requirements

The software design for sensor nodes usually needs to be accelerated, robust, fault-tolerant, occupying a small memory capacity, and bears high energy optimization for the evaluation of dynamic environmental data. The software needed for the nodes belongs to three categories:

The Operating System: This handles operations like booting and the general management of the overall functioning of the node. Tremendous research has been carried out in this area in terms of support for real-time applications, scheduling, computation, and memory requirements [37]. Some widely used operating systems for sensor nodes are:

- **TinyOS:** An open-source, component-based, application-oriented, and low-power consuming operating system for an embedded system such as WSN that comes in a size as small as 400 bytes. It is written in nesC language and was released in the year 2000 as a joint effort between the University of California, Berkeley, Intel Research, and Crossbow Technology. The latest version is 2.1.2 [38].
- **Contiki:** An open-source and portable operating system that is relatively small in size and was developed by Adam Dunkels in 2002. It is an event-driven OS written in C with a GUI and consumes only 2kb of RAM and 40kb of ROM. It supports Internet Protocol connectivity as well as IPV6 addressing [39], [40], which, in turn, made it more popular. The most recent version is 3.0. Moreover, it comes with the world's smallest web browser, and micro-controllers from TEXAS Instruments and Atmel use this in their boards.
- **Nano-RK:** An open-source, Real-Time Operating System (RTOS) [41] for WSN that is related to micro-controllers from the Carnegie Mellon University. Nano-RK reinforces multitasking, networking, and priority-based request processing. The term "nano" implies that it is small – needing only 2kb of RAM and using only 18kb of ROM – while "RK" stands for resource kernel. It supports both critical and non-critical real-time applications. It is written in C and runs on the Atmel-based FireFly sensor networking platform – the MicaZ motes as well as the MSP430 processor [42].
- **Mantis: A**n open-source embedded operating system for wireless microsensor platforms. MANTIS earned its name from the **M**ultimod**A**l System for **N**e**T**works of **I**n-Situ Wireless **S**ensors. It is written in C as well. It is lightweight and requires less than 500 bytes of memory. A big part of the design features of MOS is its flexibility in the form of cross-

platform support and the ability to test on PCs, PDAs, and different microsensor platforms. It upholds remote management of in-situ sensors through dynamic reprogramming and remote login and advanced sensor OS features like multimodal prototyping, dynamic reprogramming, and remote shells. MANTIS is still in its growing phase, and a number of improvements need to be done in terms of power management as well as certain key factors, although some support for real-time applications is also present [43].

The chain of the introduction of an application-oriented operating system for WSN is currently developing and more is to be added to the list in the future. Other WSN operating systems include OpenTag, LiteOS, Raspberry Pi OS, ERIKA Enterprise, and more.

Besides an operating system, a sensor node is often customized by using certain proprietary or free software as required to be used easily by a non-technical person. In this case, a range of software programming languages and developmental tools are utilized. Some types of simulation software – such as NS2, Cooja, OPNET, TOSSIM, MATLAB, etc. – are also used to replicate the behavior of large WSN before actual deployment. Such software can either be sold with or without hardware by the company, and these provide an interface to program the micro-controller by using one of the most common programming languages such as “C,” “Python,” etc. Software like Excel, Python, and R are used to analyze the sensor data and draw meaningful conclusions to be able to study the pattern of data. LabVIEW and Arduino IDE are a few examples of popular sensor programming and circuit setting software.

Laboratory **V**irtual **I**nstrument **E**ngineering **W**orkbench (LabVIEW) is a 30-year-old commercial tool by National Instruments™ that is used for engineering, configuring, testing and controlling hardware, and enabling rapid data insights. The latest version of LabVIEW NXG is capable of smart real-time testing, quick automation of hardware, customizing tests that are tailor-fit to one's specifications, and easy viewing of measurement results from virtually anywhere. Measuring and designing systems with sensors and actuators has become quite convenient with LabVIEW [44], [45].

Arduino IDE: The **Arduino** **I**ntegrated **D**evelopment **E**nvironment is the most common open-source and user-friendly developing environment. Writing and uploading code to the Arduino boards or other cross-platform boards like Nanonode. Nanonode and the environment is written in Java and is based on processing and other open-source software. The current stable version is ARDUINO 1.8.12. There is an ideally defined list of alternatives to Arduino IDE, and the user is free to choose from this. These are comprised of Eclipse, Visual Studio, or IntelliJ, Programino, embedXcode (for Macintosh OS), Ktechlab, Codebender (cloud-web based platform), Visual Studio + Visual Micro (Microsoft Visual Studio), Zeus IDE, Atmel Studio, and ArduinoDroid (for Android platform) [46–48], among others.

Data storage and management software (e.g. MongoDB, NoSQL, and more) and other cloud-based platforms (e.g. Hadoop, Oracle, Amazon, Google, among others) play a vital role in preserving voluminous information for future possible references.

Power management issues are pertinent at the software level as well. This is explored through minimizing the communication and messaging overheads with the help of enhancement in communication and data forwarding algorithms. Duty sharing scheduling schemes, smoother terrain, short distances from the source to sink, and time synchronization among the nodes have significantly helped in solving power imbalance within the network.

3.5 TYPES OF SENSORS USED FOR WSN AGRICULTURAL SYSTEM

In an agricultural scenario, a WSN system consists of a group of biochemical sensors that are either analog or digital, as well as actuators. Actuators are mechanical or electro-mechanical devices that are used to control and manage a function or a system, such as the opening or closing of a valve. Actuators are operated electrically, manually, or by air or hydraulic pressure. An actuator can be linear or rotary, and it plays an important role in coordination with various sensors that are positioned in an agricultural field – such as automated irrigation systems or variable rate applications. Erdmann Corp., Hansen Motors, E-Motion, Inc., Harmonic Drive, LLC, Bishop-Wisecarver Corp., Baelz North America, Pacific Industrial Service Co., Micromatic LLC, OTP Industrial Solutions, and Island Components Group, Inc. are some of the leading manufacturing companies of actuators [49].

Each application-oriented sensor is used for monitoring different entities – like moisture, rain, temperature, etc. – that work with the defined architectural principles. Sensors can be classified into roughly three categories [50]:

1. Passive, omnidirectional sensors
   These types of sensors are capable of measuring a physical quantity at the point of the sensor node in the target field. These merely serve the purpose of detecting and do not manipulate or alter the environment by active probing. Some examples of such sensors are thermometer sensors, light sensors, vibration sensors, humidity sensors, chemical sensors, and smoke detectors. Power is required to convert the analog signal into digital. Also, the measurements taken by these sensors do not involve the notion of "direction." These sensors are rather common and are used in automation tasks for sensing.
2. **Passive, narrow-beam sensors:**
   In these types of sensors, there is a chiseled notion of the direction that is taken into consideration while taking the measurements. For example, a camera or GPS sensor can take measurements in a particular direction.
3. **Active sensors:**

This group of sensors actively probes the environment – for example, a sonar, radar sensor, or certain types of seismic sensors.

With the popularity of the use of sensors in daily life, a new and innovative featured bulk of sensors is added to the basket every day. Application-specific sensors were specially designed in order to suit the needs of the agricultural fraternity. The following items are the sensors that have discovered their place in one or more operations of an automated PA setup. Any heterogeneous setup of these sensor nodes will subsequently form any of the WSN types (e.g. terrestrial, underwater, hybrid, etc.) that can help a farmer in performing various, important functions in the field. Depending on the quantity being measured by the sensor, the following are some of the sensors that have been applicable in precision farming:

3.5.1 Optical or Light Sensors

This is a group of passive sensors that are able to generate output by detecting modifications, refraction, or reflection in the electromagnetic spectrum or visible light and which ranges in frequency from "infrared" to "visible," up to the "ultraviolet" light spectrum. These types of sensors identify light energy or the light photon into electrical signals (i.e. electrons). Light sensors are usually also referred to as photoelectric devices or photosensors. Phototransistors, photoresistors CMOS sensor, contact image sensor, electro-optical sensor, flame detector, infrared sensor, LED as a light sensor, light-addressable potentiometric sensor, fiber optic sensors, optical position sensor, thermopile laser sensors, photoelectric sensor, scintillometer, and photodiodes are some of the more prevalent types of light intensity sensors [49], [51].

3.5.2 Electro-Chemical Sensors

Electro-chemical sensors are mobile electronic devices that determine changes in current, voltage, or the presence or composition of gas or liquid chemicals, and

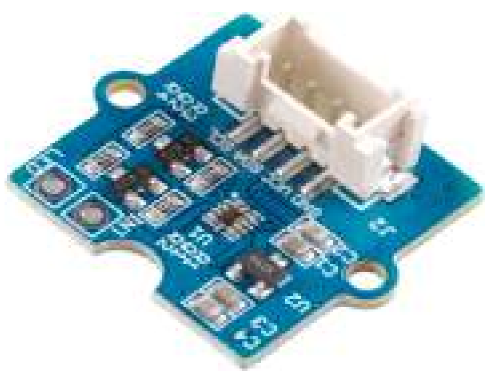

FIGURE 3.8 Grove Sunlight Sensor [51].

these convert the readings into visual outputs. A chemical sensor based on the recognition of biological material is called a **biosensor.** A biosensor is an analytical device that detects the presence of a chemical substance that is formed through interaction of a biological component – for example, tissue, microorganisms, organelles, cell receptors, enzymes, antibodies, nucleic acids, and beyond. Electrochemical biosensors may be classified into any of the succeeding categories: amperometric biosensors, potentiometric biosensors, impedimetric biosensors, and voltammetric biosensors. Other categories of biosensors include optical biosensors, wearable biosensors such as the SmartWatch heart rate monitor, thermometric biosensor, and piezoelectric biosensors [52], [53]. The first "true" biosensor was developed by Leland C. Clark, Jr. in 1956 for oxygen detection. Biosensors bear a great scope in precision farming when it comes to monitoring soil microorganisms, water toxicity, disease detection, and environmental monitoring. An emerging area of interest is where sensors are designed to direct surveillance of the airborne or other genetically modified organisms (GMO) disease-causing agents [54]. Such nodes are efficiently designed to detect quality, ripening, and yield prediction on a real-time basis. For example, *M. Croceipes* exposes caterpillars attacking cotton crop; Graphene Sensors can detect the presence of a virus thus can help in identifying viral plant disease-causing agents [55]

3.5.3 Electro-Mechanical Sensors

Devices that work on the principle of electro-mechanics and include both electrical and mechanical components in carrying out functions are referred to as electro-mechanical (EM). Mechanical action (motion) will result from the electric energy or vice versa. The electro-mechanical sensor market for agriculture includes sensors like pressure, flow, motion, level, leak, or accelerometer sensors among many more.

Pressure sensors are electro-mechanical devices that detect forces per unit area in gases or liquids and provide signals to the inputs of control and display devices.

Motion sensors are electronic devices that can recognize movement.

Level sensors are electro-mechanical devices that are used for determining the level of liquids, gases, and/or input signals to the inputs of control or display devices. Leak sensors are electronic devices used for identifying or monitoring the unwanted discharge of liquids or gases. Gas sensors fall in this category, but more accurately for CO_2, H, O_2 gas detection. Such sensors have been extremely useful in revealing the amount of gas in cereal storage units [56].

Flow sensors ascertain the movement of gases, liquids, or solids. These sensors mostly use ultrasonic principles for the detection of events.

3.5.4 Location or Proximity Sensor

Proximity Sensors are electronic devices that are used to detect the presence of nearby objects while omitting any point of contact. A proximity sensor can detect the presence of objects usually within a range of up to several millimeters, and, in doing so, produce a usually dc output signal to a controller. The different types of proximity sensors include inductive proximity sensors, capacitive proximity sensors, ultrasonic proximity sensors, photoelectric sensors, hall-effect sensors, and more.

As their name implies, location sensors distinguish the position of something. These types of sensors provide "positional" feedback. The position is determined either by using the concept of "distance" or "rotation." Both linear or rotational sensor nodes are available in the market [57].

3.5.5 Weather and Moisture Sensor

The water content that is present in the soil is referred to as soil moisture. Several methods like the gravimetric method, nuclear method, and dielectric method are used to measure soil moisture. In the dielectric approach, several probes are created to measure the dielectric constant under the working principles of the time-domain reflectometry method, resistivity method, capacitive method, and frequency domain reflectometry. Examples of such probes include the Watermark™ Sensor and Gypsum Sensors (US$2–30), ECH20 (US$80), and TDR Probes (US$500–1000).

Temperature sensors detect thermal parameters. A temperature sensor typically relies on an RTD or thermistor to measure the temperature of gases, liquids, or solids and convert this into an output voltage.

Humidity is the presence of water in the air. Humidity sensors work by detecting the water in the air according to the changes in electrical current. There are three basic types of humidity sensors: capacitive, resistive, and thermal. All of these three types will track minute changes in the atmosphere in order to calculate the humidity in the air [58]. Rain, leaf wetness sensors, and many more exist in this category.

3.5.6 Vision and Imaging Sensors

Vision and imaging sensors are devices that detect the presence of objects or colors within their fields of view and convert this information into a visual image for display. CMOS Sensor and other camera sensors are examples of this class.

3.5.7 Smartphone-Based Sensors

These types of sensors are present in our smartphones – for example, ambient light sensors, touch sensors, gyroscopes, accelerometers, etc. As many precision farming operations – such as fertilizer application, soil study, irrigation requirements, etc. – involve the use of mobile phones, such sensors easily come in handy, and a farmer need not purchase extra sensors if he is able to get updates about his crops from a remote sensor network [59]. There is a distinctive and vast range of sensor devices, and everyday need-based innovative devices are added to the list [60]. Due to the tremendous amount of examples on the topic, discussing and mentioning each device is out of the scope of this book.

3.6 INTELLIGENT SENSORS VERSUS SMART SENSORS

The concept of smart sensors and intelligent sensors was first introduced by NASA [61] in the process of developing a spaceship, and this successfully created a product in 1979. Spaceships and similar rocket testing require a significant number of sensors to detect data such as temperature, position, velocity, and altitude. Sensors called “smart sensors” have a microprocessor, a sensor, an analog interface, and an analog to digital converter (ADC) that are used to identify changes and parameters, whereas “intelligent sensors” are referred to as sensors that have various intelligent and independent functions such as self-testing, self-validation, self-checking, self-diagnosis, self-adaptation, self-identification, self-calibration, self-compensation, among others [62–64]. These two types of sensors, thus, only differ in terms of type of function and hardware components. The features of intelligent sensors include:

1. High precision
2. High reliability and high stability
3. High signal-to-noise ratio and high resolution
4. Strong self-adaptability
5. Higher performance and price ratio
6. Sufficient amount of storage capacity to store high-quality data

3.7 IMPACT OF THE WIRELESS SENSORS ON TRADITIONAL AGRICULTURE

The increase in food production is a growing present-day need. Indeed, there are many challenges in producing a surplus amount of food from the field. This will lead to overexploitation of the current resources of arable land; therefore, tremendous use of agrochemicals has become a source of hope for the farmer who intends to grow more food. However, this habit will lead to regretful effects on the environment. The science and engineering associated with the use of advanced electronic technology in traditional agricultural practices revolves around the increase in productivity in a sustainable way but also with a decreased burden on the environment. An array of eco-friendly networked sensors will serve as the foundation, and this will help in elucidating critical spatio-temporal patterns of the field, trends in climate, plant ecophysiology, and hydrology, thus recording the response and actuating an automatic response in a real-time fashion and at a minimal cost. Remote sensing that interprets information indirectly from the electro-magnetic spectrum and satellite motion that is dependent on the frequency of data has made RS rather inconvenient for real-time and continuous monitoring of farms [65]. For example, a small number of sensors will cover an area, as in one sensor per 100 meters by 100 meters. Precision agriculture is an emerging area, where sensor-based technologies have foreseen a good scope and form from the fundamental element of a PA setup. Monitoring and managing the functions of a field based on the information about spatial and temporal crop variabilities hold vital importance. Through the adaptation of intelligent or smart sensors in a farm, a platform has been provided for the merging and collaborative working of other hi-tech machines or tools for optimized production. Scheduling the farming tasks based on the site-specific inputs from sensors has ensured both agricultural production quantity and quality. Monitoring either acres of land or a small greenhouse with high resolution and multiple angles using a camera or an optical sensor is now possible. Accurate and early predictions of yield, disease, or other critical alerts regarding the soil or crop health have provided imperative support in minimizing loss and damage. These functions have made farming less cumbersome and more fun for people [66].

3.8 SENSOR BASED VARIABLE RATE APPLICATION

The inputs for crop or plant growth, whether in a vast or small area of farmland, depicts high macroscopic variability. Uniform distribution of fertilizers, water, chemical, or other inputs is not always required, as this will lead to cost burdens or wastage of resources and, hence, more ecological and economical burdens. Therefore, the concept of SSCM and variable rate application evolved in precision farming for determining a precise amount of inputs to crops at a definite time. The definition of site-specific crop management practice employs a strategy of meeting and managing the requirements of a specific crop on the basis of its need. The application-specific sensors installed on a farm to read designated parameters or conditions of a particular crop will facilitate and call for necessary requirements and demands for that particular crop on a real-time basis. The call for requirements can either vary spatially (i.e. in terms of space or area) or temporally (i.e. in terms of time). Sensors are the perfect and thorough choice to study such dynamic nutritional provisions behavior of agricultural setups because they provide an accurate measure of variability in real-time, and this is not possible with technologies like RS, GIS, GNSS, GPS, etc. Variable rate application has become useful in the application of fertilizer, herbicide, water, etc. [67–70].

3.9 APPLICATIONS OF WSN IN PRECISION AGRICULTURE

Data from sensors can provide meaningful insights into the flowering seasons, the effect of biotic and abiotic factors, harvesting, and many more pertinent topics without harming plants or crops [71]. A sensor network can be placed on a single Chinar tree to map the microclimatic differences over a single tree in order to study the growth interactions of the tree.

Crucial future estimations about the crop on a real-time basis are a vital part of the warning or forecasting systems. When stored in a database, the gathered information can work as a backbone for high-end analytics and can provide suggestions for the betterment of the workflow. Agricultural statistics will be

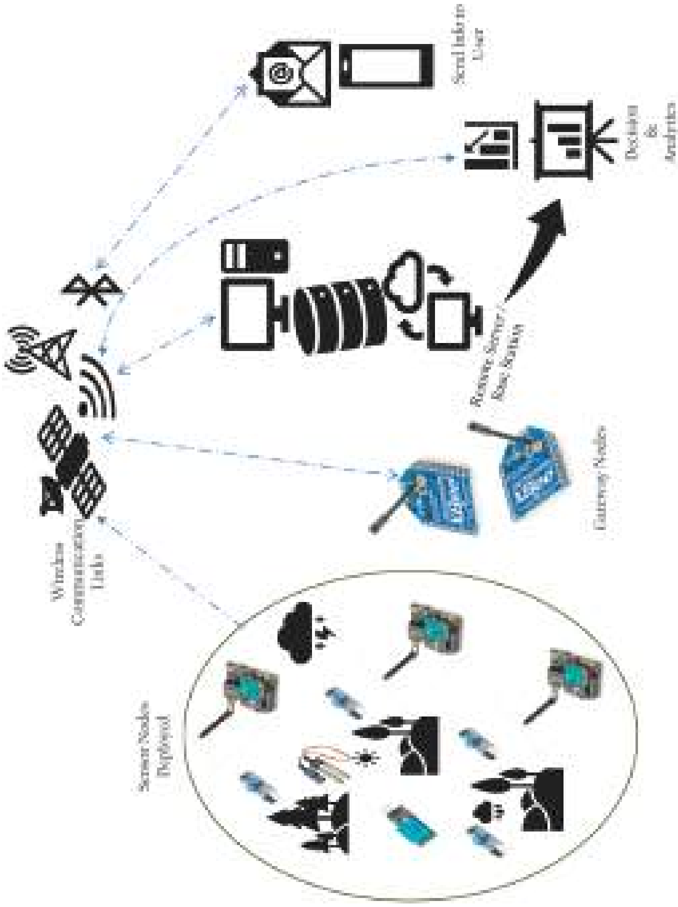

FIGURE 3.9 WSN platform for Monitoring Agriculture 5.0.

more accurate, thus the decision-making process reflects this as well. The application of sensors in PA ranges from sensing of biomass, canopy volume, crop, soil nutrients, and properties, water content, yield, disease and pest outbreak, and many more. The effective combination of sensors with other technologies – such as remote or satellite sensing, machine learning, AI, and benefit from cloud computing services have actually transformed the traditional way of farming into something incredibly more productive.

3.9.1 Soil Analysis and Characteristics

Several techniques like Near Infrared Radiation (NIR), MIR and Raman spectroscopy, spectral libraries, electrodes, thermal imaging, fluorescence kinetics, and electromagnetic radiation are available for analyzing certain properties like macro-nutrient presence (K, N, and P), moisture level, temperature, and compaction, for instance. Following the working principles of these techniques, many sensor devices have been developed [72], [73].

3.9.2 Yield Sensing

When combined with proximal ground information from the sensors, airborne imagery and remote sensing are utilized to feed and build machine learning models to predict the yield of a certain crop for that season, the monitoring of harvesting time, and each growth stage for remotely located crop sites. This application is still in the developing stage, and much work has yet to be done[74].

3.9.3 Weed Management

With the help of thermal imaging cameras and fluorescence-based sensors and mapping, real-time weed identification is useful in proximal differentiation and targetting of automated weedicide-spraying machines. Image and color-based sensors incorporated in UAVs or robots have positively assisted in crop and fruit assessment for harvesting based on ripeness. Sensor-based weed control reduced the volume of herbicide applied by 63%–85% relative to a uniform spray application [75], [76].

3.9.4 Disease Detection and Classification

For healthy and good quality production, the onset of pathogen infection can be facilitated with the use of sensors for monitoring the meteorological or other biotic components of a particular crop. Chlorophyll, leaf area index, leaf wetness, biosensors, or pH sensors have aided in the detection or prediction of the onset of various fungal or bacterial diseases. Regular application of chemicals takes place according to the inputs received and is followed by a manual inspection of the farmer. It the domain where the use of sensor technology has been extensively used [77].

3.9.5 Irrigation Management

Micro-irrigation methods – namely, drip and sprinkler irrigation – are popularly used in site-specific precision watering. With scarcity in water sources, effective water management and irrigation systems are essential in order to save this precious resource. Dealing with the under- or over-irrigation problems and leaching or drying of soil, requirement-based irrigation can be performed using Wireless Sensor and Actuators Networks (WSANs). Soil moisture, solenoid values, temperature, and pressure sensors are significant in monitoring the irrigation operations [33], [78–81].

3.9.6 Greenhouse Management

A greenhouse is a controlled environment where plants are grown irrespective of the surrounding natural conditions. In a greenhouse, every input stimulus has to be accurate and precise. The utilization of sensors such as temperature, light, humidity, airflow, CO2, and irrigation sensors helps to create a more propitious environment than that of outside, hence, generating more productivity. Remote monitoring of the actuation devices and other sensors over wireless communication links, 3G, WiFi has added more ease as well. This type of setup can be installed in the harvest storage buildings to monitor the crops or fruit health [82–84].

3.9.7 Weather Monitoring

Weather stations with different weather monitoring sensors installed such as temperature, rain, humidity, moisture, wind speed, and pressure sensors provide real-time forecasts. Based on these predictions, a farmer can plan his farming activities, thus rendering more benefits. Strategizing irrigation, fertilization, sprays, evasion of frosting and drought situations, harvesting and transportation, storage of crops, and livestock management will become conducive. Weather changing trends and alerts for specific locations are available and synced to the farmer's mobile phone or computer system through certain APIs or software for immediate action.

Other prominent uses of sensors are finding a place in agricultural drones and machinery and crop transportation and logistics. High-end robots or drones use different types of sensors for their practical functioning. The application areas of tiny embedded microscopic sensors with reliable wireless communications and low-cost powerful sensors in agriculture are only limited by our imagination, as the list goes on.

3.10 SECURITY ISSUES AND CHALLENGES FOR WSN IMPLEMENTATION

Undoubtedly, there are endless benefits and uses of WSN procurement in precision farming. Utilizing advanced technology such as WSNs will manage the land, reduce waste, and increase productivity. This will not only increase

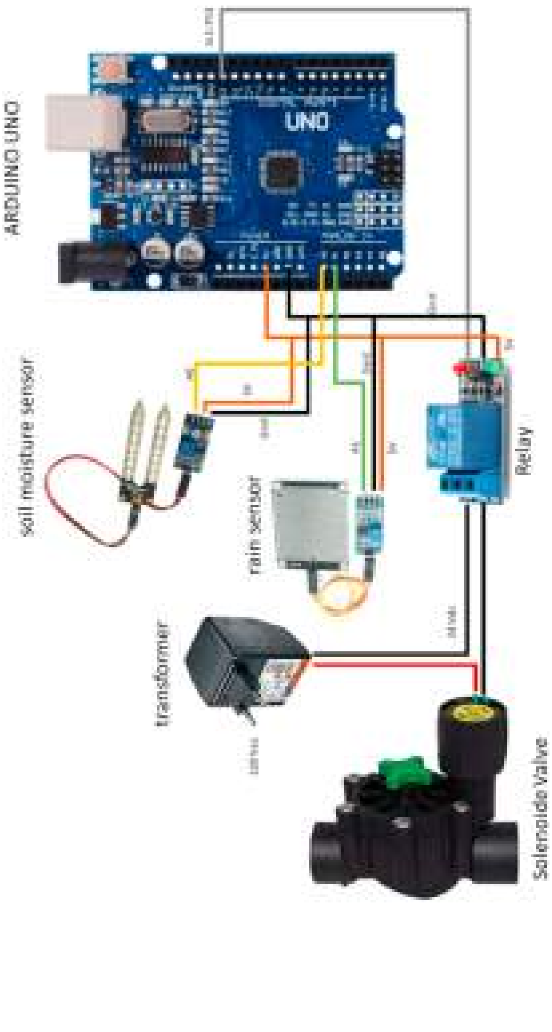

FIGURE 3.10 Architecture for WSN Based Irrigation System.

resources mobilization, but will also facilitate and promote public/private partnerships' access to the delivery of real development with agriculture as a main source of income in agriculturally backward countries.

Although wireless sensor technology is an exceptional choice for agriculture, there is still a notable amount of challenges that delay its deployment. These challenges are desisting the expansion of sensor nodes in developing economic countries, especially in the areas where there is no infrastructure, thus making it difficult for nodes to identify connectivity and distribution.

These challenges can be summarized as the following:

- Poverty and illiteracy
- Harsh environment
- Standardization problems, as there are different available technologies
- Compatibility for commercial and security reasons
- Poor IT infrastructure and inadequate technical knowledge
- Economic impact, as most companies are not ready to risk their business and invest in an unstable continent
- Security issues like corruption of data collected or theft of devices; the accuracy and error of free data is a dire need for reliable decision-making and is needed less for calibration
- Complexity of certain stages of the technology
- Lack of experienced staff
- Promotion of technical education
- Minimizing the cost of usage, which is of paramount importance
- Better enclosures to protect nodes and devices from moisture, heat, or other probable causes of damage while exposed outdoors, as well as the safe disposal of tear-out devices

There are many trial projects that are advocating wider use of integrated WSNs applications in India and other countries; however, this is still not fully implemented. To empower the use of WSNs in Indian Agriculture, global policymakers, leaders, researchers, industries, and farmers should unite to initiate collectivist opinions in order to result in different real projects. These opinions can be filtered out to produce research-based works within institutions and subsequently be offered to industries and business corporations. The industry-based projects can be simulated and tested within farms across Africa. The successful projects can be commercialized to different target groups [85].

3.11 CONCLUSION

The attainment of goals in precision farming with the implementation of sensor-based technologies have become accessible with the explosive growth and advancements in technology. Barriers in the adoption have been overcome with the help of farmers and their inclination towards smart farming. A database can be created to store this vital information that has been collected, evaluated, and then

FIGURE 3.11 HC-SR04 ultra-sonic sensorUltra-Sonic Sensor [86].

interpreted to analyze the information for future reference. With growth and cost-reduction in high-speed internet and the farmers' excessive use of smartphones in managing farming, tasks are growing rapidly. The use of smartphone sensors for plant disease detection or other forecasting is of great assistance to the growing agriculture sector. The ongoing research in the Internet of Things and the Ubiquitous Sensor Network of intelligent sensors has made this technology available anywhere, anytime, anyplace, and for everyone. Different ideas can be promoted through cooperative research work; the successful strategies can be commercialized for small, medium, and large-scale agricultural projects which will bolster economic growth. Public/private business partnerships for the inclusion of WSN in PA will not only solve food shortages but will also generate profit.

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4 IoT (Internet of Things) Based Agricultural Systems

When the desire to gain knowledge outmatches fear of failure, learning becomes easier.

— Anabia

4.1 INTRODUCTION

Over the past couple of decades, the definition of precision agriculture has been dynamic due to the introduction of integrated multidisciplinary concepts and technologies. With these advancements, precision agriculture has attained a diverse character and evolved more sophisticatedly.

There has always been an increasing demand for production to accommodate the growing population. According to FAO, it has been estimated that the world population will cross the 9 billion mark in 2050, thus creating a formidable need for food and resources. Therefore, an increase in production has developed into a Herculean task with the limitation of resources, skilled labor, and arable land.

We have learned certain notably important lessons from the past which we need to charge to experience so that we will have the capacity to overcome or to at least mitigate the consequences caused by insufficient knowledge. During the 20th century, in order to increase productivity, we focused on:

A. Mechanization
B. Improved genetics
C. High inputs

Some of these factors directly or indirectly caused ill-effects to the soil and water, as well as led to extensive deforestation and the corresponding havoc of greenhouse gases.

Currently, around 70% of the water consumption is agricultural, and there is a relatively high unsustainable level of chemical consumption which results in unstable agriculture. Hence, there is a need for PA with its primary aim being sustainable agriculture. As a flexible and multidisciplinary method, PA has proven to be one of the effective solutions to solving imminent worldwide hunger and destruction of natural resources. It also integrates with diverse domains in discovering an effective approach to tackle prevailing problems in agriculture.

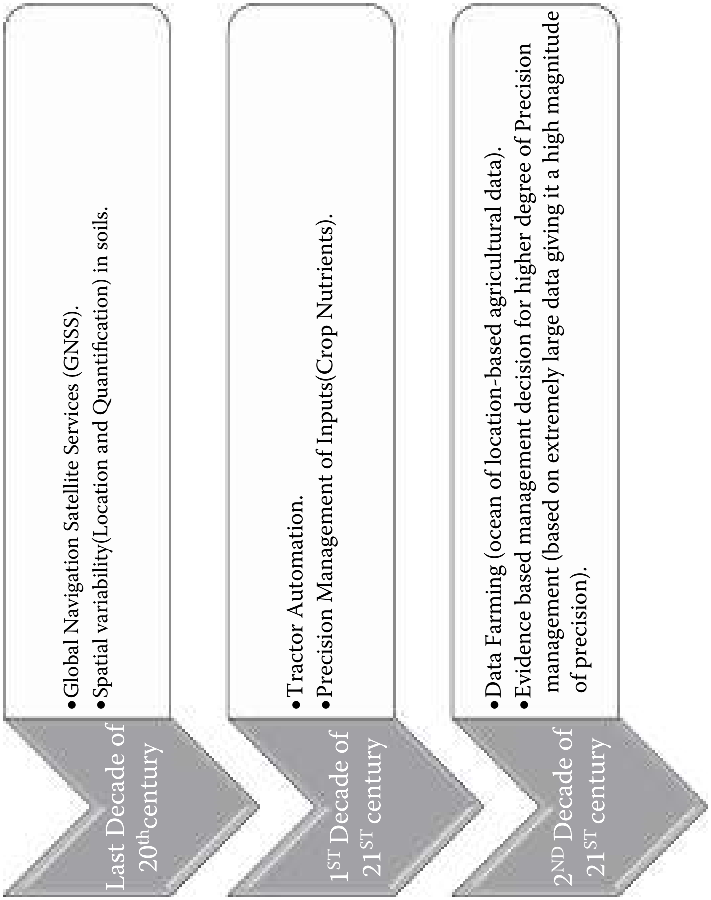

FIGURE 4.1 Timeline: PA Focus Areas

Hence, the definition of precision agriculture has unfolded with time and technology. Currently, the highest-rated definition of PA is:

> *Precision agriculture is a management strategy that gathers, processes, and analyzes temporal, spatial, and individual data and combines this with other information to guide site-, plant-, or animal-specific management decisions to improve resource efficiency, productivity, quality, profitability, and sustainability of agricultural production.*
>
> —The International Society of Precision Agriculture (ISPA) [1]

4.1.1 Internet of Things (IoT)

The term IoT was coined by Kevin Ashton in 1999, and it represents the collection of data from "things," subsequently processing it either at the individual level of "thing" or a group of "things" in any combination with the help of artificial intelligence (usually machine learning) in making efficient decisions based on huge data and the position of the source(data). This transformed farming into smart farming while, in the case of PA, only the position of data was taken into consideration for decision-making (Figure 4.2)[2].

With IoT, there is a real-time data transfer to the storage database where a pre-installed program makes precise decisions based on data knowledge that it has already been trained with and sends the correct information to the user. Conventional agriculture has revolutionized into a cyber-physical system (CPS – a combination of physical and software components). Hence, smart farming is

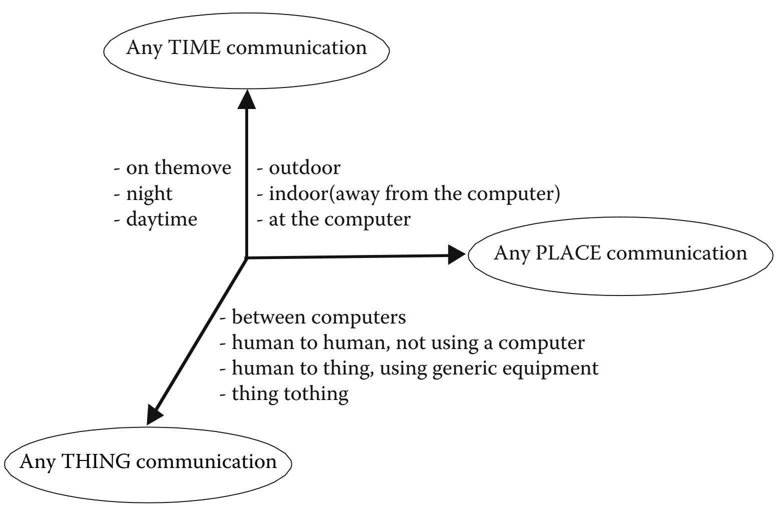

FIGURE 4.2 ITU Definition of IoT
Source: ITU, 2006.

the evolution of precision agriculture, with IoT as its foundation. IoT has tremendous scope in the agricultural sector, as the tedious job of data collection, processing, and analysis to be able to deduce competent decisions minimizes human effort, human error, waste of resources, etc. in practical terms. Remote monitoring of almost all of the parameters is now possible, and the purpose of automation in farming methodologies has become a reality by the virtue of IoT to a greater extent. Thus, IoT has reinforced smart farming [3].

When we talk about the 4IR, it is a must to discuss the IoT because it is an essential subset of it. In general, IoT refers to the assemblage of interfaces and modules (i.e. a system or sometimes, the module can itself be a system, hence making it a "system of systems"). It consists of devices, a cyber-physical system (CPS), and digital machines that are interconnected, bear unique attributes, and are capable of computing and data communication over a network using their unique network identities. IoT is gaining popularity, because it is flexible enough to include the latest types of technology and combine these with the internet [4].

It achieved prominence also due to the fact that human efforts were reduced by this technology as "human-to-human" and "human-to-machine" interactions were eliminated in IoT in terms of data collection, transfer, and processing [5].

The basic architecture of IoT consists of three layers, as shown in Figure 4.3:

The specific uses of the internet for data communication and the interconnection of "things" and the characterization of layers are done according to the work executed on data (i.e. collection and transfer) from the source and into the physical world [6], [7].

Many have contributed to the research, development, and design of IoT systems by embedding RFID, sensors, and actuators [8].

Cisco introduced the term Internet of Everything (IoE) as a system that consists of the interconnection of people, things, data, and processes. They believe that the "network effect" was the main reason why focus on IoE is necessary. Robert Melancton Metcalfe, who helped pioneer the internet since 1970, formulated a law which states that the value of a network is proportional to the square of the number of connected users of the system (n^2). This was the driving force for IoE [9].

4IR created a number of opportunities and widened the horizon for various academic and technical communities for these to contribute towards international development, transparency, and security using IoT technology in the agricultural sector [10].

With the advancement and upgrade in cyber-physical systems (CPS) and IoT, there has been an exponential demand for smart devices and IoT devices [11], as

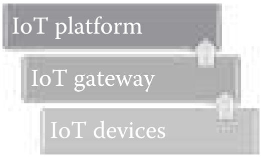

FIGURE 4.3 Basic IoT Architecture

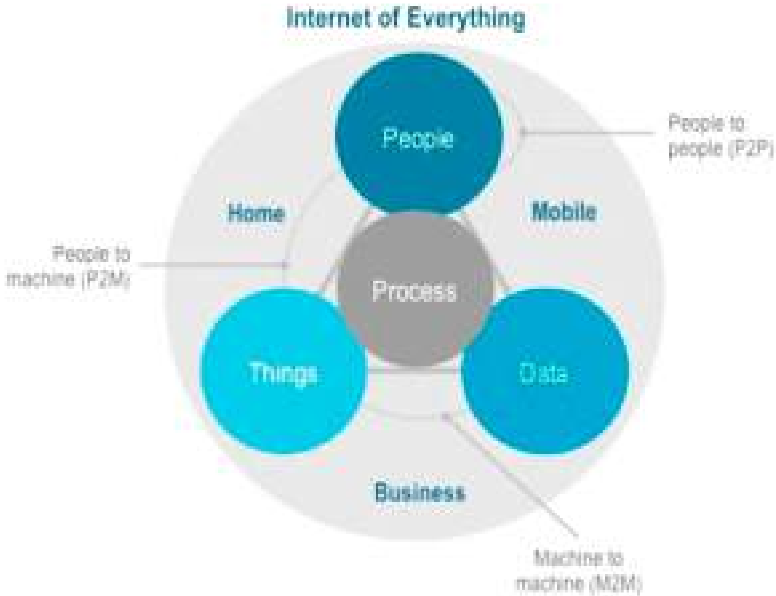

FIGURE 4.4 The Internet of Everything (IoE) [9].

these are considered the main system components that act as a bridge between the physical and virtual environments [12].

4.1.1.1 What "THING" Refers to in an IoT

ITU-T Y.2060 prescribes the following definitions to attain a clear perception of a "device" and a "thing" in an IoT:

Device: In regard to the IoT, this is a piece of equipment with mandatory capabilities of communication and the optional capabilities of sensing, actuation, data capture, data storage, and data processing.

Thing: In regard to the IoT, this is an object of the physical world (physical things) or the information world (virtual things), which is capable of being identified and integrated into communication networks [2].

After going through a large resource of literature published to date, there are three major, general views:

1. IEEE considers a "thing" simply as any physical object that is relevant from a user or application perspective.
2. Some organizations like NIST, ITU, W3C, IERC, and IETF are in favor that a "thing" can be physical or virtual, should have identities, and can be integrated into a network.
3. Edewede Oriwoh and Marc Conrad [13] have done a detailed study for defining the "thing" of IoT and have provided a detailed and elaborate definition [14].

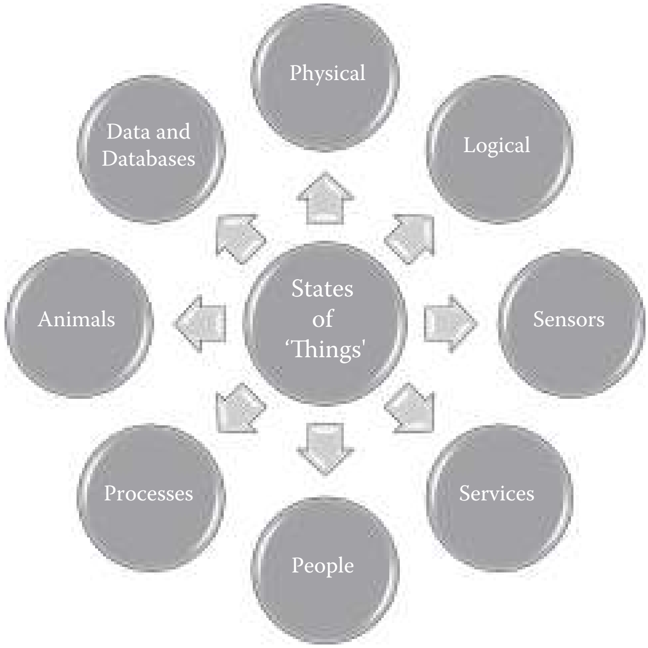

FIGURE 4.5 Different States of "Things" [13].

Table 4.1 depicts various key attributes of "THING" in various definitions:

A "thing" must have the ability to interconnect in a network with any specialized communication protocol and has the processing power to handle that communication. The "thing" in IoT may be able to perform certain actions once it is commanded, but for that purpose, it must recognize the command and confirm its completion. Routers, switches, and gateways are considered as part of the network but may also be classified as things [5]. There is a compulsion of data for IoT working that can be in the form of anything like data collected by things itself. Examples include data that is involved in various agricultural sensors like:

1. Location sensors to determine latitude, longitude, and altitude to a high precision which is of immense importance in PA
2. Optical sensors which use light to measure the soil properties like clay content, the quantity of organic matter present in the soil, and moisture content of the soil using different spectrums of light (e.g. infrared, polarized, etc.)
3. Electrochemical sensors which are used to determine pH and nutrient levels in soil using ion detection
4. Mechanical sensors that help in finding soil resistance in order to deduce the soil properties

TABLE 4.1
Definitions of a "Thing" in IoT [14]

Organizations	Keywords
NIST	• Occurs in physical or virtual space • Can be all software, all hardware, or combinations of software and hardware
ITU	• Is an object • Can be physical or virtual • Can be identified • Can be integrated into a network
IERC	• Is physical or virtual • Has identities • Has physical attributes • Has virtual personalities • Uses intelligent interfaces
IEEE	• Is any physical object relevant from a user or application perspective
IETF(Lee et al.)	• Can be a computer, a sensor, people, an actuator, a car, a book • Can be classified as three scopes: people, machine, information • Can be identified by one unique way; • An identified thing is called an object
W3C	• Can be a virtual representation of a physical or abstract entity • Can be connected or not connected • Each thing can have one or more virtual representations • Can have histories • Has identities, rich descriptions, services, access control and data handling policies • Has URIs
Oriwoh and Conrad	• Serves a purpose • Can be interconnected • Interconnections can be technology or natural methods • Has a form or is a set of structures

(*continued*)

TABLE 4.1 (*continued*)

Organizations	Keywords
	• Is traceable • Can communicate • Can be interfaced • Can have a physical or logical form • Can be living or non-living • Can be identified • Is tangible or intangible • Can be autonomous or non-autonomous

5. Dielectric soil moisture sensors enable identifying soil moisture by detecting the dielectric constant(symbol = K) of soil, which is an aspect of moisture
6. Airflow sensors which work on the principle of analyzing the pressure required to pass a particular quantity of air at a known depth to detect soil permeability
7. Agricultural weather stations which contain numerous sensors to determine air and soil temperature, rainfall, leaf wetness, chlorophyll content, wind speed, dew point temperature, wind direction, relative humidity, solar radiation, and atmospheric pressure

The data involved in the above sensors are quite useful in PA for various tasks like recording topography and boundaries which are useful when interpreting salinity maps, yield maps, and weed maps in addition to a precise overview of the features of the land. IoT aids in the efficiency and performance of the UAVs and UGVs in agriculture by making this significantly smarter. Hence, with the adoption of IoT in PA, we are certainly going to witness both predicted and unpredicted benefits that will significantly improve the agricultural sector.

4.1.2 IoT Devices and Smart Objects

The use of cognitive technologies, like computer vision and machine learning, helps us to better understand and analyze practical situations, thereby increasing precision which is necessary for agriculture in order to acquire improved yield and the efficient use of resources. IoT technologies which use cognitive computing (a subset of artificial intelligence) focus on reasoning and understanding at a higher level and in a manner that is analogous to human abilities by correlating huge data (structured/unstructured) from numerous sources like location sensors, optical sensors, electrochemical sensors, mechanical sensors, dielectric soil moisture sensors, airflow sensors, etc. to provide certain valuable information to the user and suggest highly precise changes or actions necessary to improve efficiency.

TABLE 4.2
Definitions of a Smart Object [14]

Authors	Definitions
Sterling	• Space-time, location-aware, environment-aware, self-logging, self-documenting, uniquely identified object • Provides data about itself and its environment
Korteum et al.	• Autonomous physical/digital object augmented with sensing, processing, and network capabilities • Carries chunks of application logic to make sense of its local situation and interact with human users • Senses, logs, and interprets what is occurring within itself and the world • Acts on its own, intercommunicates with each other, and exchanges information with people
Fortino et al.	• Autonomous, cyber-physical • Augmented with sensing/actuating, processing, storing, and networking capabilities • Metadata model with attributes – identifier, creator, physical property, type, device, service, operation, location, QoSparameter
IPSO	• A specified collection of reusable resources such as physical type, static, and dynamic properties
Lopez et al.	• Possesses a unique identity • Is able to sense and store measurements made by sensor transducers associated with it • Is able to make its identification, sensor measurements, and other attributes available to external entities, such as other objects or systems • Can communicate with other smart objects • Can make decisions about itself and its interactions with external entities

It is vital to understand what actually we refer to by the terms that are frequently used in an IoT-based agricultural system so that there is no misconception about terminology like smart object, smart sensor, and IoT "thing." Furthermore, in the upcoming topics, definitions from various researchers

TABLE 4.3
Comparison of the Key attributes for Smart Sensors, Smart Objects, and Things in IoT [14]

Entity	Key Attributes
Smart Sensors	• A physical device with network interface • Sensing only • Local data storage • Local data processing
Smart Objects	• Physical or virtual objects with network interface • Sensing only or with actuator • Local data storage • Local data processing • Interaction with other objects
IoT "Things"	• Physical or virtual objects with network interface • Sensing and actuator • Local data storage • Local data processing

and organizations have been proposed so as to gain a clear idea of different views.

It should be apparent that an IoT device may not be a smart object at all, because, in order for a device to be smart, it needs to fulfill certain conditions. Various definitions of smart objects are presented in a tabular form below [1]:

Table 4.3 illustrates a comparison of the key attributes for smart sensors, smart objects, and "things" in IoT:

4.2 ARCHITECTURE OF IoT

In order to understand the IoT as well as to discern the processes involved, it is necessary to study a general model that describes the elements of IoT at various levels [1]. There are several models of IoT which exist today, but, in order to fulfill the purpose of this book, the reference models mentioned below are essential from an agricultural perspective. In the year 2014, a joint initiative of Cisco, IBM, Rockwell Automation, along with others resulted in the formation of a committee which framed the standardized architecture of IoT [15]. This is termed as an IoTWF reference model, and the IoT World Forum (IoTWF) is an annual industry event that is hosted by Cisco [16].

The key characteristic of this model is that it is centrally controlled; the center is usually cloud-to-end points. The flow of data is from endpoints towards the center where it is then processed; however, there also might be decentralized processing that is, therefore, acting as a cloud service. The division of the model consists of seven layers because, when encountering situations wherein its goal is to create a customized IoT for a specific purpose, knowing the role of each layer along with the interfaces required will aid in the task of easily establishing an IoT system. Hence, many institutions can contribute elements for different layers while having adequate interoperability. Another benefit of this model is that security can be patched at any desired layer specifically [15], and this makes IoT simple and approachable [17].

These seven layers include:

1. **Physical devices and controllers**
   This is the first layer which consists of IoT things, IoT devices, objects, smart objects, sensors, smart sensors, and also includes controllers (the definitions of which have been discussed in the earlier sections of this chapter). Therefore, their main aim is to collect the data, bear the ability to transfer this upstream, and be capable of performing commands with the help of actuators.
   The example of this layer includes a simple sensor with its driver (both hardware and software) [1], [15].
2. **Connectivity/networking**
   This layer refers to the connectivity of the IoT entities (IoT things, IoT devices, objects, smart objects, sensors, smart sensors, and also includes controllers) to the network and includes all of the methodologies, technologies, and tools to establish connectivity in the IoT system. This includes both wired and unwired modes of connection in IoT entities as well as a control system which is usually a cloud service.
   The decision-making process is not confined to a specific layer/level; rather, it depends on the situation. For example, if a device is able to make a decision locally, then it can perform the action of its own and only notify the IoT platform in case of a complex situation. The decision-making takes place at many levels in the IoT system, thus making it a "liquid" process [1].
   Thus, the function of this layer is to act as a reliable and secure passageway for data and to forward this to the upper layers where filtration, analysis, accumulation, and valuable information from this data is deduced. Switching or routing is done in this layer and if required, translation and coordination between protocols are also possible [15]. This also includes security at the network level (e.g. an application of network security policy) and may have the feature of networking analytics or self-learning) [17].
3. **Edge/fog computing**
   This layer is called the edge layer or fog layer because edge computing or fog computing takes place here, and its primary function is data cleaning,

FIGURE 4.6 IoT Reference Model of IoTWF [18].

aggregation, and processing. In this case, processing may include evaluation, formatting, expanding/decoding, distillation/reduction, reduction, and/or assessment.

Its function is to begin the conversion of data into information so that this can be further processed and stored at the next level.

An efficient system should initiate processing nearer the edge so that data traffic is reduced, thereby making the system faster to respond in real-time [17], [15].

Edge computing and fog computing are further discussed in the later sections of this chapter.

4. **Data accumulation**

   Data generated in the first layer is transferred through a network in the second layer, and particular processing takes place at the third level. Up to this level, data is considered to be in motion, and the speed of transfer is dependent upon IoT system configurations. The processing of data does not need to necessarily be in real-time for an IoT application.

   Therefore, the function of this layer is to prepare data for storage – specifically, the conversion of event-based data to query-based data so that it can be retrieved on queries after accumulation.

5. **Data abstraction**

   This is also primarily a data-oriented layer. As the size of data hikes up, more storage systems are required, and data from different sources is sometimes required to be stored separately. Useful datum (singular of data) is termed as "information". Furthermore, an adequate amount of information required to turn a decision into "knowledge."

   The data at this level is aggregated from multiple storage systems and made "consistent, complete, and validated" so that it is able to respond to a query and return with a valuable outcome [1], [15], [17].

6. **Application layer**

The IoT reference model does not strictly define an application because this varies to a great extent. In this case, the information from the fifth layer is interpreted. The application can achieve the desired goal by virtue of its multitude of features consisting of services and web platforms. For the development of the application, definitive techniques in which recurring software elements can be used are preferred so as to avoid the inconvenience of developing new software.

When the customization of a particular application is not possible, then only the end-user can build its application according to the human-machine interaction chosen by keeping this component under focus only. Given below are the different purposes which various applications aimed at achieving:

- Monitoring device data
- Controlling devices
- Combining device and non-device data
- Handling simple interactions (mobile application)

- Analytics
- System management/control center (controls the IoT system itself and does not act on the data produced by it) [1], [15], [17].

7 **Collaboration Resources and Processing**

In order to properly benefit from the information achieved from the IoT system, it is necessary for it to conclude something valuable. For this purpose, it is necessary to have collaboration among resources and processing. People use the applications and acquire benefits according to their own requirements. This also paves the way for various business opportunities. Thus, people are often involved at this level, including the business sector.

Some examples include:

- The workflow management system
- The DSS (decision support system)
- The systems for process simulation [1], [15], [17].

4.2.1 Simplified Reference Model of IoT

I. **IoT Layer** – This layer is comprised of:

a. IoT sensors
b. Actuators

II **IoT Network Layer** – This layer includes all of the networking components which help in connectivity and data transfer, as per requirement. It includes the following:

a. IoT gateways
b. Switches
c. Routers

We put fog/edge elements under this heading. The main goal of fog/edge computing for the data analysis to take place in closer proximity to the IoT things because this makes processing faster and reduces the network traffic. Low latency and quicker responses are its key features. An example of this is IoT healthcare.

III **IoT Cloud and Application Layer** – This layer helps in data management and the processing of such data. It is also responsible for the management of IoT devices and the general IoT system [19], [20].

4.2.2 Four-Stage Internet of Things Architecture

The plinth for Stage 1 of this architecture is the IoT things that pass a wide range of inputs. These inputs help in building a large dataset of linked informational context [21].

I. Stage 1:
This is the first or the primary stage of this architecture, and it consists of sensors and actuators which receive "data or information" from the "things." The aforementioned "data or information" is converted into digital form for further processing.

II. **Stage 2:**
Data acquisition systems and internet gateways that carry out important functions are commenced in this stage. This works by collecting all of the types of data from various input sources and converting this into a convenient form for further processing. This stage is also responsible for A/D (analog to digital) measurements and control. The IoT gateway is a part of this stage that enables communication and, therefore, all of the communication data needs to pass through here.

III. **Stage 3:**
This stage is also referred to as the "edge," and the process here is called "edge computing." The "data or information" from the second stage is received through various gateways either by wired or wireless transmission.
Usually, the edge receives data by wireless modes such as WiFi, LoRa, or ZigBee. An important characteristic of good architecture is to process data closer to the ends; thus, pre-analytical processing takes place here to aid in subsequent processing [22–24].

IV. **Stage 4:**

The final stage of this architecture is where the actual processing is done and converges into a cloud. Data analysis, data management, and some data archival are its main characteristics. After processing the data, analysis is done according to the purpose, and valuable results are obtained which help in control, management, and decision-making.

4.2.3 IoT Architecture Implemented in Agriculture

After presenting the general IoTWF reference model with other types of architecture, it must be clear how the various components and layers coordinate and synchronize in order to make an IoT system fully functional [21]. To reiterate, the aim of this book is to provide all of the necessary information and knowledge to the reader to help him/her in this current scenario where technological awareness has turned into a requirement. Until the end of 2018, the sensor-based agriculture market stood at US$1.8 billion globally and is expected to rise to US

$4.3 billion by 2023 at a Compound Annual Growth Rate (CAGR) of 19.3% [25].

This section will provide all of the essential details of the technical terms that we have come across in IoT technology. This shall be explained from an agricultural perspective to facilitate easy understanding.

The various practically implemented IoT systems to date in the agricultural domain can be understood quite easily if studied in three layers of architecture:

I. **IoT Device Layer**
   In order to understand the IoT system, the first layer that must be studied is one that is comprised of IoT devices – those that we first encounter because these devices are intentionally distributed at particular locations in the environment to gain inputs [26]. These devices are capable of sensing and actuating the physical environment [27].
   According to a standard procedure or protocol, this collected information is transferred to an IoT gateway layer [11], [12]. By virtue of the interconnection of these devices among themselves and the internet, this enables the IoT system to use a cloud server along with its services which constitutes the third layer of the architecture (i.e. the IoT platform layer) [28].

II. **IoT Gateway Layer**
   As the name suggests, this layer helps connect the IoT devices layer with the IoT platform layer, thereby acting as a "bridge" which can be in the form of software or hardware. In simpler terms, it connects the sensing and actuating device of the IoT system to various types of platforms and applications in a secure manner. Thus, it adds to the overall security of the IoT system. The IoT gateway allows the communication of "things" in IoT systems such as those commonly found in industries, smart cities, as well as in agriculture also, among other things [29].
   Some IoTs can have gateway-centric architecture when specific M2M interactions are needed [30].
   Presently, there are certain smart IoT gateways that are able to overcome connectivity issues in order to join a heterogeneous network, Zigbee Adhoc network, cable network, and wireless LAN [31].

III. **IoT Platform Layer**

The IoT Platform layer is not a single layer but rather, a set of layers and is often termed as "middleware." It is a dominating part of the IoT system as it enables the following:

a. Application support to an IoT
b. IoT device management
c. Supervised and controlled data flow
d. Application management system

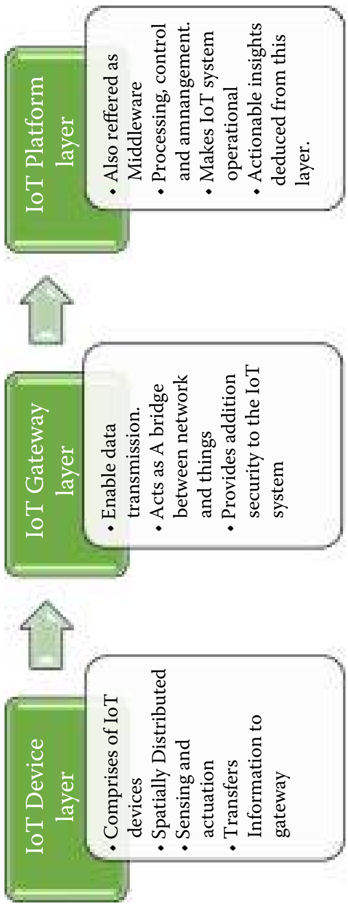

FIGURE 4.7 Three-Layer IoT Architecture

IoT solution services, management of IoT services, and the automation of IoT "things" are only possible due to the IoT platform layer. There are many open and proprietary sources available worldwide that boost IoT solutions development.

Examples of IoT platforms include:

i. Platforms which provide an end-to-end solution
ii. Platforms that provide connectivity
iii. Cloud platforms
iv. Data platforms

In agricultural IoT platforms, the farmer and subsequently, the developer is aware of the problem and opts for such a platform which depends on the type of attributes and defined system functions. This should possess the following features [32]:

A. Enablement of necessary data collection
B. Ability to store and manage the same data
C. Mandatory provisions for processing data
D. Applicable analytical models and visualization techniques in order to provide meaningful and actionable conclusions

4.3 BRIEF OVERVIEW OF IoT NETWORK

In order to ensure maximum benefits from the implementation of an IoT system in an agriculture-related domain, general awareness about the IoT network is necessary so that implementation, its maintenance, and corresponding security become easy for the user even if it is not his/her specialization [15]. It should also be clear that the IoT network is comprised of two main parts:

a. Internet
b. Edge network

Both differ in characteristics and also have different functions. Simply put, an edge network can be understood as a network of all of the "things" which can be anything like sensors in the field, objects, vehicles, instruments, devices, etc. which are connected to an IoT system. Each IoT assumes the environment as a constraint because it affects the network to be adopted as well as the number of nodes and their respective spatial position. For example, sensors deployed in a vast area sometimes cannot be powered by a grid. For this specific constraint, it should be able to utilize/consume any locally available source.

All of the parameters in edge networks are bound to the outcome that is required by the user and, hence, can illustrate a large deviation in the functioning of each parameter. A couple of examples are listed below:

a. **Data transfer rate**: Some sensors usually have a low data rate in an edge network in comparison to the one where real-time video is to be transmitted and, thus, involves large data.
b. **Delay in storage and processing**: Usually, a large and dynamic delay in storage and processing is acceptable in edge network; however, in the case of a control application and alarm notification, the delay should be at the minimum and constant.
c. **Error rate:** This factor is also considered in choosing an application.

We sometimes refer to IoT applications as a "system-of-systems" as it enables the interaction of many independent systems (or nodes) for a rather insightful result [33].

Gateways are the nodes that connect the edge network with the internet using certain protocols. These help in data communication between edge network protocols and internet protocols, as these possess the processing feature and, thus, aids in reducing network latency and shifts to processing closer to "things" (the concept of edge or for computing) [34].

4.3.1 ISO/OSI Model and Simplified ISO/OSI Model

ISO stands for International Organization of Standardization which developed a conceptual model called the Open System Interconnection (OSI) model [15]. It is commonly referred to as the ISO/OSI model that divides a communication system into abstraction layers. Since this is a conceptual model, this provides knowledge about communication in a network by dividing this into smaller layers. There are seven layers in the original ISO/OSI Reference Model [35].

Generally, in an IoT network, we utilize the simplified ISO/OSI model which consists of five layers, because three layers from the actual model are merged into one layer as shown in Figure 4.8 below:

In an IoT network, the term PDU is often encountered, so further explanation for this is fundamental. PDU stands for Protocol Data Unit which are data messages used for communication between the layer shown in Figure 4.9 below. Depending on the type of data involved, PDU is also referred to as "packet," "datagram," "frame," and "segment."

4.3.2 Simplified ISO/OSI Model Layers

Describing the functions of each layer in proper technical terms is beyond the scope of this book. Hence, a basic approach has been used to make the reader adequately competent to be able to at least implement an IoT system and to also ensure its smooth functioning.

1. **Application Layer**

The application layer is primarily related to the exchange of application data that takes place at the end nodes and defines the type of message that gets transferred.

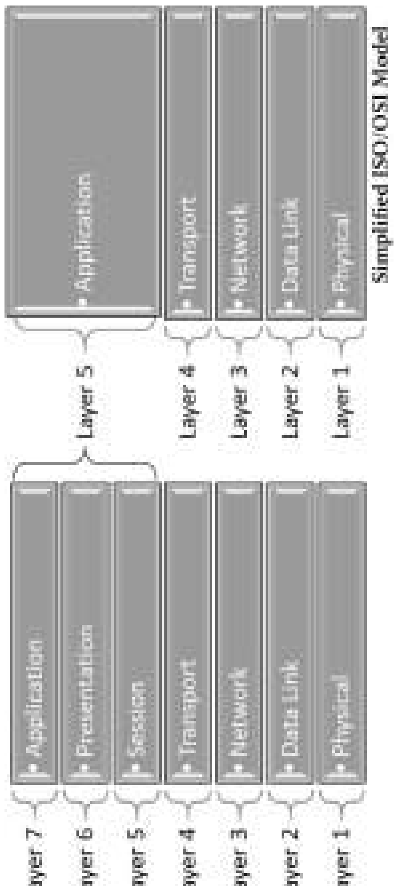

FIGURE 4.8 ISO/OSI MODEL and the Simplified ISO/OSI Model

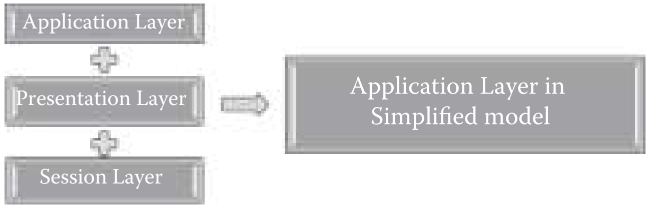

FIGURE 4.9 Merged Application Layer in Simplified ISO/OSI Model

This layer is actually a combination of three layers in the ISO/OSI model as shown in Figure 4.9:

In the ISO/OSI model, the objectives of the two merged layers are the following:

a. Presentation Layer*:* data representation and encryption
b. Session Layer: session establishment, management, and recovery

2. **Transport Layer**

The transport layer's function is to tag an address to various processes that run in the application layer. Two commonly used protocols in the transport layer are:

a. TCP/IP: Transmission Control Protocol
b. UDP/IP: User Datagram Protocol
   Both protocols have their pros and cons; accordingly, opinions about one being better than the other have arisen.
   These protocols are used according to the specific issue that we need to address along with other constraints in the IoT system – such as the need for data fragmentation (when data is large), data acknowledgment, mode of transmission used in the system, available energy, required latency, security, etc. [36].

3 **Network Layer**
The network layer's function is in routing which is carried out by using two common Internet Protocols (IPs): IPv4 and IPv6. The IPv6 is the latest version and has advantages over the IPv4. In order to get a PDU transmitted, there should be a source as well as a destination address that is linked to it as this helps in the routing process.
In simple terms, we can compare the IP address with the sender and the receiver address as that in a conventional post system.

IPv4: It has 32 bit address size that is usually
represented in a dotted decimal notation.
Example: 169.149.42.34
IPv6: It has a 128 bit address size usually represented in a

hexadecimal notation.
Example: 2405:205:8d:8d13:9d8b:12e:1328:943a

4 Data Link Layer

The main task of the data link layer is the Identification of the node interfaces and regulation of access to the medium. There are two main methods used in the data link layer, as illustrated below:

i. Carrier Sense Multiple Access (CSMA)
ii. Time Division Multiple Access (TDMA) acquired from telephone networks

5 Physical Layer

In the context of this book, an elaborate and fundamental description of the physical layer of the ISO/PSI model is compulsory. It is responsible for the transmission in the medium. While addressing the practical situation regarding IoT in agriculture, the user should be aware of the working and features of different modes of data transmission in this layer. Usually, an IoT application uses certain portions of the electromagnetic spectrum referred to as "frequency bands." For transmission, a particular frequency band is used so that it is not altered/interfered with by any other transmission, because two different frequency bands can work simultaneously. Two transmissions at a simultaneous frequency band during one time is not possible.

So as to have maintained balance and to avoid any technical conflict, the government regulated the allocation of the EM spectrum. The frequency bands that the government issues to any specific organization are called licensed bands. These are usually cellular network providers.

The remaining bands can be used at one's own discretion but only if these satisfy the following conditions:

i. $\underset{\text{(transmitted radiated power)}}{\boldsymbol{P} < \textbf{\textit{Threshold}}}$

ii. $\frac{\boldsymbol{n(PDU)}}{\boldsymbol{TIME}} < \textbf{Threshold}$

(number of PDU transmitted per unit time)

These frequency bands are known as "unlicensed bands" which *can* occupy any slot in the EM spectrum, and these are commonly used in LANs and PANs. The frequency determines the nature and behavior of the signal. In some transmissions, like that of WiFi where the frequency is 2.4GHz or 5GHz, the sender and the receiver should be in the line of sight (LoS). The higher the frequency, the higher the data is carrying capacity of the signal.

In order to implement an effective IoT system to achieve a required goal in agriculture, choosing a network standard involves governing factors like:

I. Bitrate: low-frequency network standard when low bitrate is needed
II. Range: dictates the type of network standard to be used
III. Environment: presence of obstacles can hinder transmission and, hence, the network standard is chosen accordingly [15].

4.3.3 Standardization Bodies

In order to avoid chaos and confusion, it is must to set certain standards and thus, standardization bodies are necessary. These are organizations that coordinate the development of new standards. These can be area-specific, like the Institute of Electrical and Electronics Engineers (IEEE) which is concerned with electrical and electronics engineering and computer science.

Some of the standardization bodies are mentioned below:

- 3GPP: The Third Generation Partnership Project [37].
- ITU: International Telecommunication Union [38], [39].
- IEEE: Institute of Electrical and Electronics Engineers [40].
- ISO: The International Organization for Standardization [41], [42].
- ETSI: The European Telecommunications Standards Institute [43].
- IETF: The Internet Engineering Task Force [44].

4.3.4 Some IoT Network Technologies and Standards

1. **Modbus:** Modbus is a communication protocol developed by Modicon systems. In simple terms, it is a method used for transmitting information over serial lines between electronic devices. The device requesting the information is called the Modbus Master and the devices supplying information are Modbus Slaves.

Various Modbus protocols are given below [45]:

a. Modbus RTU
b. Modbus ASCII
c. Modbus Plus (Modbus + , MB + , or MBP)
d. Modbus TCP/IP or Modbus
e. Modbus over TCP/IP or Modbus over TCP or Modbus RTU/IP
f. Modbus over UDP

2 **Near-Field Communication (NFC):**
Near-field communication (NFC) is a type of radio-frequency identification (RFID) technology. NFC enables devices to communicate when brought in proximity of four centimeters. This is also known as NFC/CTLS (contactless) or CTLS NFC [46], [47].

3 **Bluetooth**

Bluetooth is a wireless technology standard that is used for exchanging data over short distances [48–50].

Bluetooth Versions: All of these are compatible with previous versions. Some of the important versions of Bluetooth are:

- Bluetooth 1.x
- Bluetooth 2.x
- Bluetooth 3.0
- Bluetooth 4.0
- Bluetooth 5.x

4 **IEEE 802.15.4**
The IEEE 802.15.4 standard is comprised of physical and data link layers for the low-rate wireless personal area networks (LR-WPANs) [51]

5 **ZigBee**
ZigBee is a network standard for wireless connection that is used under low power and low data rates which are favorable in personal area networks (close range) and are based on IEEE 802.15.4 [52–55].

6 **ZigBee IP**
Zigbee IP is a type of wireless mesh network that works under IPv6 protocol and provides smooth connectivity for low power economical devices. This was the first open standard to work in IPv6 for a wireless mesh network [56].

7 **WirelessHART**
The HART (Highway Addressable Remote Transducer) Communication Protocol is a hybrid "analog and digital" industrial automation open protocol. WirelessHart is a type of HART with wireless connectivity [57].

8 **ISA100.11a**
ISA100.11a is an alternative to WirelessHART when considering the process control feature. This was created by the International Society of Automation (ISA) [57].

9 **WiFi (IEEE 802.11 family)**
WiFi belongs to the IEEE 802 family which provides the LAN protocols in the physical layer and the data link layer of the simplified ISO/OSI model for WLAN (Wireless Local Area Network). It works mainly with 2.4GHz and 5GHz bands but can also work in some other frequency bands [58], [59].

10 **LoRaWAN**
LoRaWAN is often used in IoT agriculture systems due to its wide area of coverage in creating low-power wide area networks (LP-WANs). LoRa is the name given to its physical layer [60–64].

11 **6LoWPAN**
6LoWPAN is LoWPAN which has IPv6 protocols. It is, therefore, a low-power wireless personal area network working on IPv6 [65–67].

12 **Z-Wave**

Z-Wave works by the propagation of low energy radio waves in a mesh network for device-to-device communication along with wireless control thereof [68].

13 **Optical Wireless Communications (OWCs)** [69]
Signal transmission takes place with the help of unguided light (visible, UV, infrared regions). Visible Light Communication (VLC) is a type of optical wireless communications in which the visible region of the spectrum is used to carry signal [70], [71].

14 **Thread**
Thread is a networking protocol for low-power, embedded consumer, and commercial IoT devices that use IPv6. Initially, it aimed to prevent single point failure in mesh network [72].

15 **Cellular Network Standards**

There are numerous devices that operate on wireless mechanisms while using radio waves for signal propagation; an example of which is mobile phones. These devices can receive signal from many cell site base stations.

- **Second Generation (2G** cellular technology) [73]
- **Third Generation (3G** wireless mobile telecommunications technology) [74]
- **Fourth Generation (4G** broadband cellular network technology) [75]
- **NB-IoT** [60], [76] (Narrowband IoT Cellular Technology): It is a low-power, wide-area network radio technology standard that was developed by 3GPP.
- **LTE Cat M1:** LTE Category M1, LTE Cat M1, or simply LTE-M is a 4G profile specifically designed for IoT and M2M communications.
- **Fifth Generation (5G):** 5G is the latest generation of cellular mobile communications [77].

4.4 CHARACTERISTICS OF INTERNET OF THINGS

The following characteristics are according to the International Telecommunication Union (ITU) Telecommunication Standardization [78] and ISO/IEC 29182-1:

1. **Interconnectivity**
The most important characteristic of IoT is that it should have the ability to connect anything to global information and a communication infrastructure.
2. **Things-related services**
IoT should have the ability to provide privacy and semantic consistency in thing-related services.
3. **Heterogeneity**
These characteristics of an IoT enable diverse types of devices despite having different protocols and hardware and network platforms to

intercommunicate. These devices can also connect to a service platform that belongs to an outside network.

4. **Dynamic changes**
   This characteristic refers to the flexibility of the device in altering its functions according to the environment. These changes can be with respect to the space and time of work [79]; it can also be the number of active devices.
5. **Enormous scale**
   There can be a large number of devices connected in an IoT generating massive data that needs to be managed and further processed for applications.
6. **Data gathering and processing by things**
   IoT devices pre-process collected data. Furthermore, services are provided either directly from the device itself or through a service provider. It evident that sensor network technology is one of the key enablers for IoT services
7. **Collaborative data processing**
   An important quality of an IoT system is the ability to solve a complex problem with the collaboration of many "things" in the system. The collected data can be pre-processed at the same device or by some other device in the system. Particular information can be gained from preprocessing, and this may be shared among various devices. Next, data fusion is required to gain valuable insights.
8. **Maintenance-free operation**
   It might be necessary for the IoT system to function without human intervention for an extended period of time. Accordingly, the IoT device must be either maintenance-free or has the ability to be remotely maintained.
9. **Self-adaptation**
   The devices in the IoT system should be smart or intelligent in order to adjust for changes in operating conditions as well as capable of optimizing resource management and functionality.
10. **Energy efficiency and operating lifetime**
    For a device to run longer, the energy consumption of the device should be efficiently managed. Hence, energy harvesting tools and technologies increase the operating lifetime of the devices.
11. **Application domains**
    Some of the IoT application domains are given in the table below. It should also be noted that the domains can work in coordination with a combined IoT system.
12. **Ubiquitous**
    Availability of and access to information at any time and any place through the connected IoT devices of the network is possible. This characteristic encourages the addition of various devices [79].
13. **Interoperability**

TABLE 4.4
Rec. ITU-T F.748.0 (10/2014). Some Examples of IoT Application Domains [78]

Domains	Description	Examples
Industry	Activities involving financial or commercial transactions among companies, organizations, and other entities; These include business to business (B2B) and business to customers (B2Cs)	Manufacturing, logistics, service sector, banking, financial governmental authorities, intermediaries, etc.
Environment	Activities regarding the protection, monitoring, and development of all-natural resources	**Agriculture and breeding**, recycling, environmental management services, energy management, etc.
Society	Activities/initiatives regarding the development and inclusion of societies, cities, and people	Governmental services towards citizens and other social structures (e-participation), e-inclusion (e.g., elderly, disabled people), public transportation, etc.
Home	Activities concerning individual and family members	Health monitoring for oneself (weight, sleeping hours, etc.), nutrition care by monitoring of diet taken by family members using a cloud database

The ability to support many different types of standards and protocols so as to make an IoT system fully functional is one of its main characteristics.

14. **Sensing and actuation**

It is the principal characteristic of an IoT to detect various parameters in the external environment surrounding the device in addition to device monitoring. Also, the actuation of the devices is of immense concern which helps in working and adaptability [79].

4.4.1 Various IoT Platforms for Smart Agriculture

FarmBeats

FarmBeats is an end-to-end IoT platform for agriculture that enables seamless data collection from various sensors, cameras, and drones [80]. FarmBeats is a low-cost and readily available IoT platform for agriculture. It supports high bandwidth sensors using TVWS – which is a low-cost, long-range technology.

FarmBeats uses a weather-aware solar-powered IoT base station and an intelligent gateway that ensures that services are available in both the cloud and while offline. It also incorporates new path-planning algorithms that extend drone battery life. FarmBeats is an IoT platform that meets the objectives in a highly variable and resource-constrained environment.

SmartFarmNet

SmartFarmNet is an IoT platform for smart farming applications that permits effortless integration and the use of virtually any IoT device, including commercially available sensors, cameras, weather stations, etc. (also known as a "bring-your-own IoT sensor principle") 81. This reduces sensor installation and maintenance costs, while providing an easy upgrade to newer and more advanced sensors. It supports scalable data analytics that can continuously process large crop performance data. This platform also offers do-it-yourself tools that allow plant biologists and farmers/growers to analyze and visualize plant performance data.

SmartFarmNet was developed by a multidisciplinary Australian team that included crop biologists, computer scientists, growers, and farmers. SmartFarmNet is the largest system in the world (in terms of the number of sensors attached, crops assessed, and users it supports) that provides crop performance analysis and recommendations. Moreover, SmartFarmNet provides tools for fast and scalable data that can cope with the enormous velocity of data (i.e. big data) that is generated from hundreds of thousands of IoT sensors.

Infiswift

The Infiswift IoT platform combines an innovative edge-to-cloud connectivity and analytics software engine with robust Intel architecture.

thethings.iO

thethings.iO is the IoT application enablement platform that enables fast and scalable connection of things to the internet with multiple protocols, beautiful dashboards, and strong APIs [82].

Raspberry Pi

Raspberry Pi has been emerging as the IoT platform of choice recently. Raspberry Pi is a rather affordable computer that runs on Linux, but it also provides a set of GPIO (general purpose input/output) pins that allow the user to control electronic components for physical computing and to explore the IoT with a range of connectivity options up to 8GB of memory storage [83,84]. Comparatively, it is more powerful and faster than other IoT boards and can handle complex functionality, including data-heavy audio and video streaming.

It operates in an open-source ecosystem, as it is closed-source hardware (the board itself is not open hardware) [84] that is cost-effective, versatile hardware that has gained huge community support as tons of already ported IoT projects adds to its appeal. It can run a host of operating systems, such as Raspbian (Raspbian is open-source and runs a suite of open-source software or Debian Linux), Android, Windows 10, IoT Core, etc. Raspberry Pi has various models classified under each of the following families [85]: Raspberry Pi, Raspberry Pi 2, Raspberry Pi Zero, Raspberry Pi 3, Raspberry Pi 4.

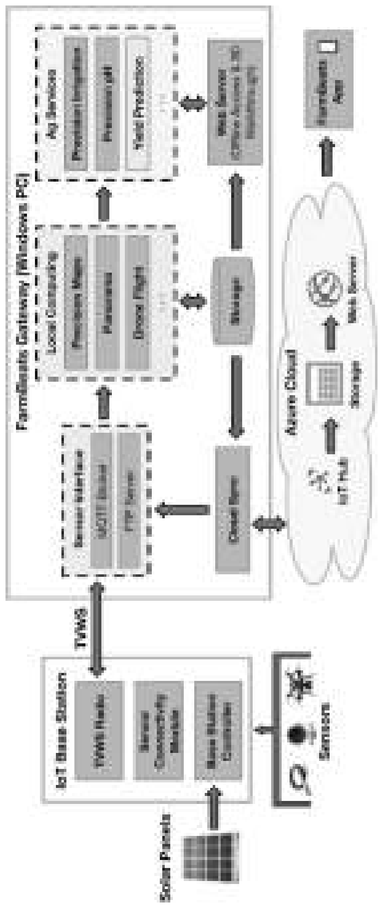

FIGURE 4.10 FarmBeats System Overview [80].

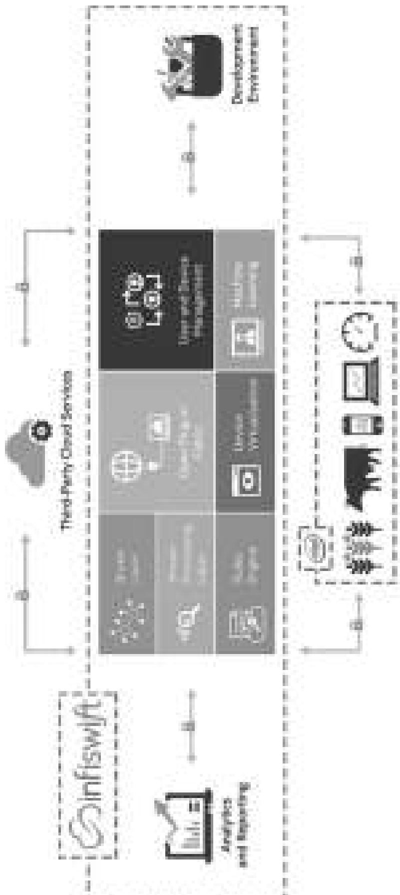

FIGURE 4.11 Infiswift connects physical products to each other and the cloud to enable the agriculture industry to gather, analyze, and act on relevant data.

FIGURE 4.12 Thethings.iO Functions [82].

FIGURE 4.13 Raspberry Pi 3 Model A [83].

Amazon Web Services

With Amazon Web Services (AWS) IoT, Amazon offers a managed, cloud-based solution. Platforms and software are all offered as a service, with the ability to scale and use its analytics tool on IoT data [86]. AWS has broad and deep IoT services, ranging from the edge to the cloud. AWS IoT cloud vendor brings together data management and rich analytics in easy-to-use services that are designed for IoT data with significant noise. It bears multilayered security features like encryption and access control to device data, as well as a service to continuously monitor and audit configurations.

Arduino

Arduino has been linked with agriculture for a legitimately long time. Arduino is an open-source hardware platform composed of a series of electronic boards that are equipped with a microcontroller [87]. Arduino is a simple-to-use IoT platform that has an appropriate blend of IoT hardware and software. It operates through an array of hardware specifications that can be inured to interactive electronics. The software of Arduino appears in the plan of the Arduino programming language and the Integrated Development Environment (IDE) for programming the microcontroller. The recently released Pro IDE is comparatively more convenient and enables faster coding [88]. All of the software supplied is free, and the circuit diagrams are distributed as free hardware [1].

Kaa

The Kaa IoT platform is an enterprise-grade IoT enablement technology that permits walking safely into the agriculture IoT field [90]. By tying together different sensors, connected devices, and farming facilities, Kaa streamlines the development of smart farming systems and provides maximum flexibility for a custom-tailored architecture design. Kaa is perfectly applicable for single-purpose smart farming products such as smart metering devices, livestock trackers, or failure prediction systems as well as for multi-device solutions – among which are resource mapping and farming produce analytics solutions. Kaa is built on a modular microservice architecture that allows for any necessary modifications, extensions, or integrations.

4.4.2 The Hardware

After a considerable development in the field IoT, there are currently numerous hardware components of IoT that help in prototyping and are capable of different levels of functioning like development boards, for example [91]:

a. Arduino
b. Beagle Board
c. Pinoccio
d. Raspberry Pi
e. Cubie Board

The structural components of these development boards are the following:

FIGURE 4.14 ARDUINO NANO 33 IoT [89].

i. **Microcontrollers** (**MCUs**): These are the processing units of the device and act as a storage area. MCUs are integrated circuits (IC) that contain a processor, Read-Only Memory (ROM), and Random-Access Memory (RAM). Examples include ARM, Intel, Broadcom, among others.
ii. **General-Purpose Input/Output** (**GPIO**) Pins: There are a number of GPIO pins that serve both digital and analog.

The modular combination of various development boards benefits communication, the formation of new sensors, new actuators, and more for advancing an IoT device. There are plentiful types of sensors that are used in IoT. Examples include pH sensors, airflow sensors, potentiometers, proximity sensors, soil moisture sensors, infrared sensors, vibration sensors, biosensors, etc. Sensors are usually wired into the microcontroller where the IoT device operations take place.

4.4.3 Operating Systems

In an IoT system, it is possible that a "thing" may not require any operating system, while some may require a real-time operating system (RTOS) depending on the efficiency, security, and purpose to be served. RTOS implements process and memory management and supports various services [91].

When an IoT system must be installed, there is a thorough investigation of all of the components, and selection is done only after it is ensured that these outmatch the necessary criteria. However, the detailed information about the operating systems in IoT is beyond the scope of this book.

Basic knowledge of the operating systems that are used in agricultural IoT is necessary as this facilitates the user to choose an appropriate system that will best serve the purpose. In some cases, security is of paramount importance, so the operating system used should have a high level of security architecture, and the corresponding devices should support this level of security. Examples of these RTOS are Contiki, Android Things, RIoT, Apache Mynewt, Huawei LightOS, Zephyr, Snappy, TinyOS, Fuchsia, Windows IoT, TizenRT, Raspbian, Amazon FreeRTOS, Embedded Linux, Mbed OS, and beyond.

Security and privacy are of prime importance as it is highly unsuitable for an operating system to procure security flaws or to allow any breach in privacy.

4.5 INTER-OPERABILITY CHALLENGES

The term "interoperability" in IoT can be considered as a requirement of an IoT system [79]. As the recent decade has witnessed an exponential development in this field, nowadays, we refer to "interoperability" as the characteristic of an IoT that serves the actual motive of the IoT to connect every other "thing." By the virtue of interoperability, it is now possible for a large number of diverse devices to be connected and intercommunicate, thus becoming a functional part of IoT. To date, there has been significant, ongoing research in this field to make interoperability of various types of IoT components possible. A number of standards and protocols are being worked on and have been worked to make devices interoperate. To understand in greater depth, interoperability has been broadly classified into three types as shown in Figure 4.15 below:

1. **Technical interoperability**
   This is understood as the congruity between the hardware of the IoT system with all of its "software components." In other words, the software should be flexible enough to support a diverse range of hardware devices and to be compatible with these [92].
2. **Syntactical interoperability**
   In an IoT network, for devices to communicate, it is necessary that D2D (device-to-device) messages should have a defined syntax. The type of message format can range from bit tables to high-level languages like HTML, XML, Java Script Object Notation (JSON), comma-separated variables (CSV), and electronic data interchange (EDI) [92–94].
3. **Organizational interoperability**

The global- IoT infrastructure and the vastly distributed system have been possible only due to the capability of IoT systems to communicate valuable and meaningful data despite certain highly fluctuating systems. Open connectivity has been enhanced to handle all types of interoperability challenges [95–97].

4.6 APPLICATIONS OF IoT IN SMART AGRICULTURE

As previously mentioned in Chapter One of this book, there is an increasing demand for food and the need to feed the enormous population of the world, and IoT has proven to be the best solution to date. IoT is the solution to a large number of problems that are otherwise not solved. The obstacles in agricultural production due to environmental changes can be mitigated by the adaptability of IoT systems. Some of the recent and common applications of IoT in agricultural specific domains are the following:

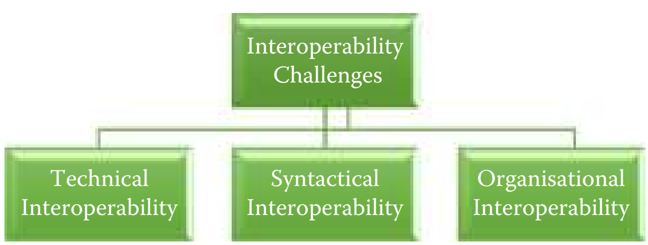

FIGURE 4.15 Types of Interoperability

1. **Solar-Powered Automated Drip Irrigation System**
   Agriculture irrigation accounts for 70% of water use worldwide [98,99]. Conventional methods of irrigation are inadequate in checking field losses. Irrigation, both excessive and deficient quantities, can cast a negative impact on agriculture.
   IoT provides the solution of reducing water wastage and, at the same time, helps in reinforcing VRT for fertilizer application. In this system, a network of sensors deployed in the field called the IoT-DEVICES are used for detecting various parameters of the field, and these sensors use solar energy as their power source, thus, making them energy efficient at the same time. This system works by determining the soil moisture content, feeding the data to the processing units of the IoT system (processing units can vary for different IoT systems), and so providing irrigation precisely in the field.
2. **Agricultural Drones**
   Drones are some of the sophisticated inventions that have various applications in different domains [100]. Drones, when merged in an IoT system, are highly beneficial in agriculture both in traditional as well as innovative practices. Drones can be used in precision spraying, field surveillance, monitoring crop growth, soil and ground investigation, chlorophyll content determination, nitrogen content determination, and high-definition pictures for various purposes analysis, among others. Crop yield monitoring from the data obtained from drones can be further processed and analyzed to deliver beneficial insights. GIS technology increases the efficiency of these drones in performing precise agricultural practices.
3. **Precision Farming**
   The most important application of IoT has been precision farming, as the principles of precision farming were brought to reality. Precision farming has been discussed in detail in Chapter 1 of this book. In this section, however, some of the domains for IoT implementations have been highlighted. This has gained the attention of reputable industries and organizations all over the world. A notable amount of research is being done in this field [100].
   IoT is now easy to install and easy to operate. The information available through the IoT cloud services have been so compelling that this is utilized in artificial intelligence. The IoT has enabled real-time monitoring for the farmers, and now, he/she can receive information and remotely access these devices. These economically feasible IoT systems are available in the market and have further increased the success of this emerging trend of precision farming [101].
4. **Smart Cultivation**
   Smart cultivation is boosted by the IoT system implemented in a certain field because, in a broader sense, the DSS (decision support system) is reinforced by IoT [100]. In cultivation, IoT minimizes wastage by

calculating the adequate amount of input requirement. The harvest field can be monitored, and smart systems in IoT benefits the farmer by reducing human efforts.

5. **Green House Production**
   With IoT in action, greenhouse shortcomings have been greatly mitigated [101]. The WSN that can be installed in the greenhouse can detect the environmental conditions and transmit this data to a storage location; after which, analysis is done on this data using countless sophisticated tools and analytical models. Monitoring becomes easy; remote access to various elements like the irrigation system, light intensity system, temperature control system, etc. is now possible. Now, a farmer can manage a number of processes through a smartphone [100].
6. **Monitoring Activities**

In order to gain an expert suggestion from agronomists, it is necessary for there to be continuous monitoring of various parameters of both the field and the crops [101]. Manually, it is not possible to oversee things in such a manner. Accordingly, IoT provides an edge in supervising all of the aspects of agriculture and provides this data to the expert so that reliable advice can be framed for a farmer.

The main parameters of agriculture that need to be monitored are the following:

a. **Irrigation and Water Quality Management**
   A smart irrigation system is essential for smart farming. For this purpose, soil moisture content and temperature data is constantly determined by sensors and is passed to a processing unit, or it can be processed at the sensor itself sometimes. Real-time water quality monitoring is also done with the help of the same IoT system. Hence, irrigation and water quality management become more convenient.

b. **Monitoring Weather**
   Weather plays an important role in the yield gained from the crops. Therefore, in order to avoid any damage due to weather, it is necessary that we continuously monitor air, temperature, humidity, pressure, light intensity, rain, speed, and the direction of the wind so that prediction is done based on this data. Consequently, a farmer can determine the right time and never encounter unfavorable environmental conditions. Wireless sensor networks (WSN) is a preferable choice for weather monitoring [102].

c. **Monitoring the Soil**
   Moisture is paramount for crop growth, as there is a water requirement for crops as nutrients are also supplied to crop through it. Moisture in the soil is efficiently determined by some types of sensors, and it once required serious human efforts. In addition to reducing water wastage, an automated irrigation system can also be used to identify the macronutrients

(i.e. nitrogen, phosphorus, and potassium). For farmers manually performing this test, it is a tiresome process. IoT enables farmers to receive information about the soil conditions and remotely monitor the field with information about soil requirements and corresponding useful suggestions for the amount of input.

d. **Monitoring the Farm**

The agricultural industry provides a large number of options that are related to farm management. Some of these include cattle farms, poultry farms, beehives, etc. IoT has revolutionized these fields altogether, and the impact on agriculture may be direct or indirect.

With the introduction of IoT in agriculture, there has been a lot of improvement in this sector. People have come up with brilliant and innovative ideas. An example of such an idea was to prevent the attack of animals in fields. Known conventional methods were not substantial enough, so IoT and cloud-based technology were used, and this notably reduced the loss of lives in this specific case [e-Device for the Protection of Agricultural Land from Elephant Attacks in Odisha: A Review] [79].

7. **Crop Management**
   Crop management is an important task when it comes to increasing the production and quality of the crops [101]. For this purpose, historical data plays a key role in crop management. Precision agriculture requires knowledge that is acquired from a deeper analysis of the data so that every action bears maximum efficiency. Some of these examples include water quantity required, time of watering, amount and time of fertilizer and pesticides application, etc. Under a sophisticated IoT-based management technique, real-time information reaches the farmer via an email or SMS, whichever is more convenient, and this has taken crop management to the next level.
8. **Agricultural Machinery**
   The implementation of IoT in agriculture has changed the entire scenario [101]. As previously mentioned, the drone in the section before is an example of agriculture machinery.
   Some of the machines have direct applications, while others serve indirectly. Some are used for surveillance, replacing humans in performing agricultural practices and in monitoring various parameters. IoT enables machinery to become more competent than conventional alternatives. Taking for example a seeding device that is guided by GIS, GPS-like technologies that are connected in IoT networks provides higher precision in seeding.
9. **Disease and Pest Control**

There are diverse benefits for IoT implementation, and disease and pest control is one of the major achievements of IoT in agriculture [101]. There is approximately a 37% loss in crop production each year. The data from the IoT system is stored in a cloud and subsequently, analysis of this data done. The data is either directly shared with an expert or is rendered to a machine learning platform where the results are obtained. The predictions are done based on computational analysis. Both machine learning and deep learning are incorporated and using various algorithms, diseases, and pest attacks can be forecasted. Convolutional neural networks are also used to train the system. IoT has a feature that informs the farmer over a cellular network of his/her phone in order to take necessary action. An example includes the image processing done from pictures collected from the field to evaluate the condition of the field and the crops.

4.7 CHALLENGES FOR THE IMPLEMENTATION OF IoT IN SMART FARMING

In agriculture, implementing an IoT system faces a remarkable number of challenges, and these challenges can arise and vary according to specific situations. Generally, these issues can be classified under the following sections [101]:

I. **Selecting the Right IoT Devices (Physical Devices and Software)**

The foremost challenge in the implementation of IoT in agriculture is choosing the right devices that are to be integrated with the IoT system, which includes both physical and software components.

The following are some of the definitive challenges in choosing devices for agricultural IoT:

a. Specific devices in agriculture are generally prone to harsh environmental conditions like low/high temperatures, rain, wind, humidity, and high chances of destruction.
b. Since IoT is mostly implemented in areas where the power source is a big challenge to keep the system working, battery-operated devices or those with a longer are working times are preferred.
c. Proper **infrastructure** for processing the huge data generated by the devices is one of the most formidable obstacles, and the software tools to be used should be compatible with the devices in order to perform the suitable function necessary in a particular IoT.
d. Another challenge is to maintain uninterrupted **connectivity** with the devices against the external threats posed to these devices.
e. The **reliability** of the IoT system depends on the safety of interconnectivity among the devices; hence, the physical safety of devices is also an issue.
f. **Scalability** is a common challenge that is faced by the IoT system, as there is a limitation in each gateway as well as the protocol of supporting a particular number of nodes, as each node requires a specific identification in a network.

g. The spatial arrangement of the devices is also a hindrance to IoT system efficiency.
h. **In terms of heterogeneity, t**he diverse types of IoT devices have different interfaces and communication protocols, so there is difficulty in finding a feasible way to make this system work.

II. **Interoperability Challenges**
As explained in Section 3.5., there are different types of IoT devices and components in an IoT system that need to work in coordination with one another so as to benefit the user with the desired results. It is necessary for them to be interoperable in many aspects that have been defined earlier in this chapter.
III. **Choosing a More Efficient Middleware**
Interoperability is possible due to the middleware in an IoT network. Thus, it can be considered as software that enables interoperability by making diverse applications and services to work with one another. It acts as a bridge between the network layer and the application layer of the reference model.
IV. **Appropriate Communication Technology**

The efficiency of an IoT system depends on the communication technology opted for IoT applications. In this scenario, Wireless communications play a major role and are commonly used in IoT; however, but these have unique limitations as well. There are two types of wireless communications based on the type of frequency bands:

a. Unlicensed Frequency Bands: These mainly use the 2.4GHz ISM (Industrial, Scientific, and Medical) band for communication. These bands are less secure, include more interference, and are costly to establish.
b. Licensed Frequency Bands: These are used by cellular communications (GSM Network). These bands are reliable, secure, have good network management, and has a good quality of service. The only issue lies in cost and power consumption.

V. **Interference**

When the IoT devices in a wireless network operate in a particular frequency band, there is interference caused due to devices in the same frequency band or the operation of the devices in its adjacent frequency band.

4.8 SECURITY AND PRIVACY ISSUES OF AN IoT

To understand the security issues of the IoT implementation, Dr. Barry Boehm has explained the following relevant terms in a simpler manner:

Safety: The system must not harm the world.

Security: The world must not harm the system.

Accordingly, for an IoT system to be adequate and reliable, it should be ensured that both aspects are achieved in a proper way. The most important factor that needs to be understood is that IoT security is significantly different from and way more complex than that of conventional networks, hosts, and types of cybersecurity. This is due to the fact that it is not possible to apply the same set of guidelines or certain fixed meta-security rules because the challenge is that each IoT-device is different. Furthermore, the diversity of these connected devices develop the need for specific security recommendation for each device; hence, a unique application for each system and system-of-system in an IoT network is necessary [91].

The security of the "IoT-device" is deduced from its definition which is, "any device that has the capability to communicate either directly or indirectly over the internet and has the ability to manipulate or monitor something physical (in the device, the device's medium, or the environment), that is, the thing itself, or a direct connection to a thing" [91]. Based on this definition, IoT-device security is the function of the following:

1. The use of the device
2. The physical process or state which can be affected or controlled by the device
3. The sensitivity of the systems it is connected to

Security

Security is defined as safety from significant security threats towards confidentiality, authenticity, and integrity of both data and services [78].

Privacy

Privacy is the safety against the data collection by a ubiquitous sensor network (USN) without human users being aware of such collection. There should be proper safety to guard the information corresponding to their legal owners [78].

Security remains the most important challenge in the implementation of IoT in smart farming [103], and addressing these challenges is compulsory. Usually, an unsecured IoT is prone to data loss, unauthorized access to nodes, there sensed data, and numerous other threats. Another hurdle in securing the IoT is its insufficient memory and processing for a sophisticated encrypted algorithm.

Examples of security issues include the following [101]:

i. Device-captured attacks due to the IoT devices revealing their location
ii. Denial service attack (DoS), jamming attack, and hijack attack that occur during IoT communication
iii. Unauthorized services, data tampering, session hijacking in a cloud of IoT system

Some possible mitigative measures include [101]:

i. Encryption/decryption algorithms
ii. Key distribution mechanisms
iii. Intrusion detection systems
iv. Secure routing policies

4.8.1 Threat Types

Various threats other than data alteration are listed below, these threats are also to be addressed, and proper severity measures should be present to relieve them [15].

- Identity spoofing
- Tampering with data
- Information disclosure
- Denial or degradation of service
- Bypassing physical security

In order to ensure proper security of the IoT system, the countermeasure taken should be applied at different layers according to the type and degree of the threat that they are vulnerable to. IoT-devices, network services, cloud services, and user elements should all be thoroughly investigated for threats and must have proper provisions for cybersecurity controls.

4.9 FUSION OF CLOUD PLATFORM WITH IoT

When set up in any agricultural sector, IoT is constrained by its limited power in processing and storage. In order to overcome these basic shortcomings of IoT, a cloud platform is fused with it. Cloud has been a promising solution to problems related to handling considerable data generated from IoT "things." This has paved the way to new horizons that are related to data analysis and management. Considering the overall benefit from the fusion of cloud and IoT, it can be deduced that the efficiency and performance of the IoT system have increased by many folds. A WSN used in an IoT system helps to transfer the data from a node and then uploading it to a cloud where it is stored, processed, and analyzed.

Other than the abovementioned case, there are a number of reasons why the cloud is important in an IoT system. The table given below is not the exact representation of an IoT or cloud, but in a general sense, it may help to grasp the idea of the complementary aspects of cloud and IoT.

4.9.1 Integration of Big DATA into Smart Agriculture

The data that is being generated from the latest technologies like sensors, IoT systems, AI machines, drones, GIS, etc. in Agricultural 5.0 lead to the formation

TABLE 4.5
Complementary Aspects of the Fusion of Cloud with IoT [104]

Characteristics/Features/Roles	IoT	Fusion of Cloud
Displacement	Pervasive	Centralized
Reachability	Limited	Ubiquitous
Computational capabilities	Limited	Virtually unlimited
Storage	Limited or none	Virtually unlimited
Role of the Internet	Point of convergence	Means for delivering service
Big Data	Source	Means to manage

of agricultural big data. Even small-scale farmers contribute to big data through agricultural tools and the allied activities that generate data.

Big data holds endless applications in smart agriculture and, big data is the source of knowledge for agricultural practices to be performed with high accuracy. Agricultural data that is generated from multiple sources like satellites, remote sensing systems, IoT systems, drones, GPS technology, infrared camera, various sensors, etc. which can be in any form, including videos, images, sounds, graphical patterns, etc. can be considered as big data if it satisfies the characteristics of big data (6 Vs) [105–107].

IoT services generate a tremendous amount of big data that needs to be properly processed and analyzed to obtain vital information that can aid in various practices like the selection of inputs, increasing soil and water efficiency, predicting fertilizer consumption of any crop, etc.

Smart farming is gained from the results derived from the system using machine learning, advanced statistics, and advanced data mining tools which are excellent analytic techniques for big data. A serious number of industrial organizations have started investing in smart agriculture using big data as a substantial source for designing smart machinery. Some critical predictions that have an impact on agriculture are achieved through big data with high precision like weather prediction, yield prediction, predicting demand in the market for a crop, etc. Big data is capable of reinforcing, adding, or even replacing the knowledge that is used for various agricultural practices. The decision support systems that assist in agriculture use big data for effective decision-making. Moreover, another benefit of big data is that it has transformed agricultural businesses and enterprises which ultimately have massive contributions to smart farming. Nowadays, there are many tools for big data analytics that are available worldwide and free to use or called “open source” (e.g. Hadoop).

Hence, it can be concluded that big data used in disruptive technologies like AI, ML, DL, Blockchain, IoT, among others. has been one of the major driving forces for the transformation of precision agriculture to “smart precision agriculture” [108].

4.9.2 Cloud Platform for Agricultural Big Data Storage

The magnitude of benefits that agriculture derives from the cloud platform can be understood by using the acknowledged definition of cloud computing itself.

According to the National Institute of Standard and Technologies (NIST), "Cloud Computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing recourses that can be rapidly provisioned and released with minimum management effort or service provider interaction."

Fourth Industrial Revolution (4IR) technologies generate sizeable data and work on that data. Thus, in simpler terms, we can say that these technologies are data-driven. Particularly, in the case of IoT, we mostly have systems that generate a significant amount of data that needs to be stored somewhere. Also, processing and analysis must be done for this data, and this can sometimes be possible in an IoT network independently, but in most of the cases, we need at least a cloud for these purposes. These two technologies are distinct, but the IoT benefits are maximized by merging these with a cloud. Some of the IoT shortcomings are mitigated by the cloud, as it provides excellent IoT service management which is considerably necessary. Cloud also benefits IoT in practically supporting its applications and services.

Keeping the IoT devices updated is a crucial task, and the option of FOTA (Firm Over the Air) is easily possible with the help of the cloud. Remote updates and remote diagnoses have become less tedious, and it occurs with a lot of benefits like the reduction in maintenance and support expenses [109].

The authors of [104] have presented the limitations of IoT that have been resolved by a cloud below:

1. **Communication:** In an IoT system, data communication and application services are based on communication in its network. With the introduction of the cloud to the IoT system, results have improved in terms of data management, distribution, and most importantly, data communication. The cloud provides the support for customized applications that make monitoring, management, and other operations of an IoT system notably easier. High-speed connectivity is the factor that determines the acceleration of operations and the rate of data transfer from the edge to the cloud in an IoT-Cloud system. As the development of more efficient and faster network mediums is in progress, there are high chances of improvements that might have a significant impact on the IoT-CLOUD system.
2. **Storage:** Also in the agriculture field, IoT devices generate a large number of data that needs to stored safely. The data has a large variation in its form, as it is generated by multiple sources that are unstructured or semi-structured in nature. The cloud provides huge storage where the storage time is considerable and economical. The cloud linked to an IoT creates new horizons for data sciences that, ultimately, improve the results

in the IoT system. Data is accessible to its legal owner quite conveniently even through APIs. Cloud provides rather promising security, and their encryptions are world-class, thus making it more reliable to store data. The chances of losing data are negligible, as this not stored at a single place and has multiple backups to avoid any catastrophe.

3. **Computation:** As discussed earlier, IoT processing and the resources needed for it can become a hurdle for an IoT system's efficiency. Another stronger driving force for the IoT-CLOUD integration is that most of the complex processes cannot be handled by only the device itself even if the device is smart. There must be a node present in the IoT system that is capable of handling such processing. Thus, there occurs the issue of scalability increasing the demand for infrastructure.

Here the role of the cloud is highlighted, providing required processing and the storage which an IoT may require.

For implementing IoT and the adoption of the cloud, the necessary knowledge about the types of clouds is required as per their service. In the agricultural domain, the need for a cloud may depend upon its specific application as well as on many other constraints. Users must have enough expertise in choosing an appropriate cloud platform to serve him/her in the best possible way.

There are different types of cloud service models that are divide by NIST into three customary types [110]:

I. **Infrastructure as a Service (IaaS):** When an IoT is generally implemented in the agricultural field, the proper infrastructure for data storage and complex processing is lacking. Therefore, preferably, a cloud is introduced in that IoT system. The user can utilize this infrastructure at will and has the option to expand or terminate according to project requirements and at a cheaper rate which would otherwise be economically infeasible.

   IaaS provides services like networking, servers, data management centers, and storage which are charged as per the specific cloud resources opted for.

II. **Platform as a Service (PaaS):** The PaaS model of cloud provides many services to the applications of IoT systems. It enables the testing or prototyping of newly created applications. In agriculture, the benefits of PaaS is a huge amount that can be saved while developing a new service or application.

   In this model, a cloud offers all of the necessary components that are required for the complete construction and distribution of a cloud application, and thus, the cloud is responsible for all of the necessary hardware, software, and hosting.

III. **Software as a Service (SaaS):** SaaS is a system in which the requirement is only to be improved by the application without the need to maintain and update infrastructure and components. It has a greater flexibility solution for cloud adoption. The cost and benefit equation should be considered while choosing this model. In this model, cloud application (or other software as a service) is remotely operated by a user which are then run and processed in the cloud itself and are accessible through the network.

4.10 CONCLUSION

IoT is one of the innovative technologies that are a part of Industry 4.0. In order to deploy an IoT system in the agricultural field, one should have knowledge about the fundamentals, components, and workings of the IoT system, as described in this chapter.

IoT is a system of systems in which communication and data transfer are possible in each connected "thing." IoT has reinforced smart agriculture by the virtue of the flexibility that it possesses to connect diverse types of things. There are various agriculture-specific IoT platforms available that have made the implementation of IoT practically an effortless task. IoT has numerous applications as well as associated benefits in the agricultural arena. Agricultural IoT generates enormous data that is valuable to deduce conclusions. With proper security and privacy, this IoT technology has been an important asset of Industry 4.0 and has revolutionized the agricultural sector. With the fusion of IoT with cloud, the benefits of IoT have been leveraged due to more storage, efficient communication, and high computational power. Edge and fog computing are the recent upgrades in IoT systems that have a positive impact on the overall speed, quality, and performance of a system.

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5 AI (Artificial Intelligence) Driven Smart Agriculture

5.1 ARTIFICIAL INTELLIGENCE (AI) – INTRODUCTION

The notion of man-made creation acting as intelligent beings has existed in Greek mythology. The origin of modern artificial intelligence (AI) dates back to the time of classical philosophy which describes human thinking as a manipulation of symbols [1]. Alan Turing's question "Can Machines Think?" [2] started a new domain in computing in 1950. The term, "artificial intelligence", was first coined in 1956 by American computer scientist John McCarthy at the Dartmouth Conference. McCarthy, along with Alan Turing, Allen Newell (Carnegie Mellon University (CMU)), Herbert A. Simon (CMU), Marvin Minsky (Massachusetts Institute of Technology (MIT)), and Arthur Samuel (International Business Machines Corporation (IBM)) are known as the founding fathers of AI [3]. In the early 1950s, problem-solving and symbolic methods were the most researched areas of AI. In the 1960s, the Department of Defense in the US started to develop curiosity in training computers that mimick human behavior. All of these efforts built a path for today's world of automation along with the power of reasoning of computers that supports incorporating human behavior in them [4]. From the year 2000, the AI revolution started and made its entry into homes, Facebook, Netflix, Hollywood, and other important fields to date (Figure 5.1).

The term artificial intelligence is formed with two words and has received many definitions during the past decades.

The dictionary defines "intelligence" as:

- The ability to sense
- The ability to act
- The ability to solve
- The ability to understand

Furthermore, the word "artificial" is defined as: produced or modified by human skill and labor, unnatural.

When combined the term AI is defined as:

> John McCarthy defined AI as "the science and engineering of making intelligent machines."

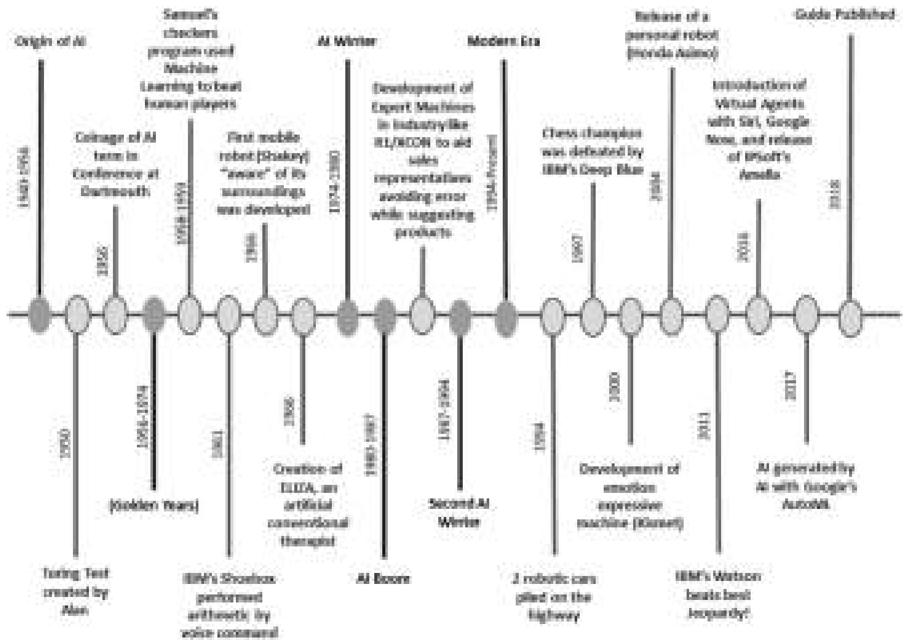

FIGURE 5.1 Evolution of AI from the Year 1930 to the Year 2000 [5], [6].

Adequate characteristics of AI include:

Norvig and Russell proceed to explore four different approaches that have historically defined the field of AI: thinking humanly, thinking rationally, acting humanly, and acting rationally [7].

Another sufficient explanation is the following:

Patrick Winston, the Ford professor of artificial intelligence and computer science at MIT, defines AI as "algorithms enabled by constraints, exposed by representations that support models targeted at loops that tie thinking, perception, and action together"[8].

Furthermore, the terminology is expounded below:

"The science and engineering of making intelligent machines, especially intelligent computer programs." It is a crossbreeding of diverse fields including philosophy, logic, methods of reasoning, the mind as physical system, foundations of language, maths, and statistics.

Finally, another acceptable definition is:

"An approach to make a computer, a robot, or a product to think how smart humans think, learn, decide, and work when it tries to solve problems."

As a result of the increased data volumes, advanced algorithms, and improvements in computing power and storage, AI, with the ability to interact with the real world to perceive, solving new problems, planning, and the capability of making decisions in dealing with unexpected problems, continuously learning uncertainties, and adapting [5], has risen to popularity. AI is all about the principle of simulating and programming human intelligence into machines in order to perform functions similar to human beings [9]. The perfect feature of AI is its ability to differentiate and define actions on the basis of their probability in an effort to achieve complex goals in the best way possible. The machines attain cognitive functions such as perceiving, learning, and reasoning and are able to solve problems like a newborn baby that is just starting to learn to categorize and recognize [10]. John McCarthy and et al. [11] advocated the following features of AI:

Automations
Language-Programmable
Calculation Size
Self-Improvement
Abstractions
Randomness and Creativity

All of the progressive work in AI started in the quest to finding answers to the above-listed features, and nowadays, AI is the most discussed, most popular, and most researched area.

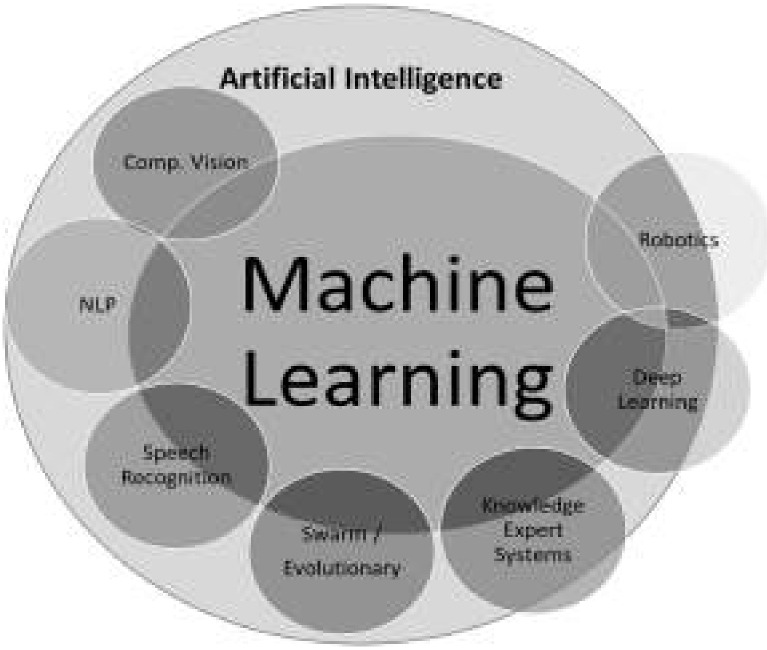

FIGURE 5.2 Different Subset of AI.

Currently, AI is the bigger concept in creating intelligent machines that can simulate human thinking capability and behavior, whereas, machine learning and deep learning are gloried to be the subsets of AI that allows machines to learn from data without being explicitly programmed [10]. Figure 5.2 below shows other subsets of AI. With these additions, AI is defined as:

> "A computer system able to perform tasks that ordinarily require human intelligence… Many of these artificial intelligence systems are powered by machine learning; some of them are powered by deep learning, and some of them are powered by very boring things like rules." [3], [5]

Artificial intelligence has become popular in the financial industry for fraud detection, self-driving cars, agricultural tractor, drones and robots [12]–[14], IoT, supply chain, health [15], education, analytical programs, decision and expert systems, smart assistants like Alexa, Siri, and many more [5].

5.2 CATEGORIES OF AI

With machine learning (ML), natural language processing (NLP), and deep learning as the revolutionary subsets of AI, the most distinctive categories of AI started to develop as discussed below [16]–[19], [20]:

5.2.1 Type I (Based on Embedded Level of Intelligence)

1. Weak AI or Narrow AI
   Weak or Narrow AI is a type of AI which is able to perform a dedicated task with intelligence. It is the most common and currently widely used AI form. Narrow AI is only able to do a task for which it is trained, and it fails beyond these boundaries. Examples include Apple Siri, Chess Playing, e-shopping recommendations, self-driving cars, and IBM's Watson supercomputer.
2. General AI
   General AI is the type of intelligence that could perform any intellectual task as efficiently as a human being. The core thought of General AI is to make machines smart like humans, with their own thinking capability. Current AI in the 21st-century world and research is at this stage, and more time and advancement are required to progress from this stage.
3. Super AI

Super AI is the level of systems intelligence in which machines surpass human intelligence and can outperform human beings in any task. This is an outcome of general AI. Although it is currently a hypothetical concept, if it is achieved, then it will change the world.

5.2.2 Type II (Based on Functionalities)

1. Reactive Machines
   Reactive machines are the oldest form of AI with extremely limited capabilities. These have no storage capacity and, therefore, are unable to learn from the past. They can only react in a limited means.
   Purely reactive machines are the most basic types of artificial intelligence. IBM's Deep Blue system and Google's AlphaGo are examples of reactive machines.
2. Limited Memory
   Limited memory machines have storage capacity for a short period of time. They can learn from past data experiences, train, and also perform the functions of a reactive machine. Various AI algorithms can be applied to large volumes of data to generate insights and enhance accuracy. The self-driving car uses a limited memory approach. Most of the present-day AI machines of the 21st century use a limited memory approach.
3. Theory of Mind
   Theory of mind AI is the next level of AI that is still under research, and no success has been achieved to date. A theory of mind level AI will be able to better understand entities it is interacting with by discerning their needs, emotions, beliefs, and thought processes. AI machines will be able to

perceive humans as individuals whose minds can be shaped by multiple factors, thus essentially “understanding” humans which is called the “Theory of Mind” in psychology.
4. Self-Awareness

Creating this type of AI, which is decades, if not centuries away from materializing, is and will always be the ultimate objective of AI research. This type of AI will not only be able to understand and evoke emotions in those that it interacts with, but also have emotions, needs, beliefs, and potentially, desires of its own. Machines will have their own consciousness, sentiments, and self-awareness. Moreover, this is the type of AI that doomsayers of technology are wary of. This is because, once self-aware, AI would be capable of acquiring ideas like self-preservation which may directly or indirectly spell the end for humanity. As such, an entity can lead to catastrophes as well. Hollywood movies like Terminator or Robocop are analogous examples of what this type of AI could develop into.

5.3 SUBSETS OF AI

Until this point, we have learned about the definitions of AI, and now, we will learn about the various subsets of AI in this section. The following are the most common subsets of AI [20]–[22]:

5.3.1 Machine Learning

Machine learning is a component of AI that provides intelligence to machines, so these can obtain the ability to automatically learn through experiences without being explicitly programmed. It consists of three types: Supervised, Unsupervised, and Reinforcement. Chapter 6 exhaustively elaborates and discusses machine learning (ML). It is the most common and popular approach of AI in the field of agriculture and beyond.

5.3.2 Deep Learning

Deep learning is a subset of AI and ML which enables a machine to perform human-like tasks excluding human involvement. It enables AI agents to mimic the human brain like an artificial neural network. Deep learning can utilize both supervised and unsupervised learning to train an AI agent.

5.3.3 Natural Language Processing

Natural language processing (NLP) is a subset of AI. NLP enables a computer system to understand and process human language such as English, whether text or speech. NLP acts as a linguistic tool incorporator for AI. With NLP, human language can actually be used to make machines learn and work. Today, AI, along with NLP, is all around us. We can easily ask Siri, Google, or Cortana to execute tasks for us in our language.

5.3.4 Expert System

Expert systems are computer programs that depend on knowledge obtained from human experts which is subsequently programmed into a system. Expert systems emulate the decision-making ability of human experts. These systems are designed to solve complex problems through bodies of knowledge rather than using conventional procedural code. One of the examples of an expert system is the suggestion for spelling errors while typing in the Google search box.

5.3.5 Robotics

Robotics has advanced into an extremely intriguing topic of artificial intelligence. For the most part, this fascinating field of innovative work focuses on designing and developing robots. Robotics is an interdisciplinary field of science and engineering consolidated with mechanical engineering, electrical engineering, computer science, and numerous others. It strategizes the design, production, operation, and use of robots. It manages computer systems for management, procurement of intelligent results, and data change.

5.3.6 Machine Vision

Machine vision is an application of computer vision that enables a machine to recognize an object. Machine vision captures and analyzes visual information using one or more video cameras, analog-to-digital conversations, and digital signal processing. Machine vision systems are programmed to perform narrowly defined tasks such as counting objects, reading the serial number, etc. Computer systems may not see in the same way as human eyes can see, but these are also unbound by human limitations and can even possess the ability to see through a wall.

5.3.7 Speech Recognition

Speech recognition is a technology that enables a machine to understand spoken language and translate it into a machine-readable format. In this form, a voice command or speech becomes the input for a computer to execute a certain task. There are particular types of speech recognition software with a limited vocabulary of words and phrases. This software requires unambiguous spoken language to understand and perform specific tasks. Today, there are various software or devices which contain speech recognition technology such as Cortana, Google virtual assistant, Apple Siri, etc. We need to train our speech recognition system to understand our language. In the past, these systems were only designed to convert speech to text, but now, there are various devices that can directly convert speech into commands.

5.4 LIFE CYCLE OF AN ARTIFICIAL INTELLIGENCE-BASED MODEL

The AI life cycle is the recurrent process that data science projects follow. It defines each step that an organization should pursue in order to take advantage of machine learning and artificial intelligence (AI) in deriving practical business value. A similar process is followed for an ML-based project. The terminologies AI and ML are used interchangeably. There are major steps in the AI life cycle, all of which are of equal importance and must progress in a specific order. The major phases in AI can also be referred to as the Planning Phase, Data Phase, Development Phase, and Deployment Phase.

1. **Define Project Objectives:** The first step of the life cycle is to identify an opportunity to tangibly improve operations, increase customer satisfaction, or otherwise create value.
2. **Acquire and Explore Data:** The second step is to collect and prepare all of the relevant data to be used in machine learning. This entails consulting domain experts to determine which specific data might be relevant in predicting the required solution, gathering that data from historical records, and getting this into a format that is suitable for analysis – most likely into a flat-file format such as a .csv, .arf, or .text. In this step, we need to identify the different data sources, because data can be collected from various sources such as files, database, the internet, or mobile devices. This is one of the most important steps of the life cycle. The quantity and quality of the collected data will determine the efficiency of the output. The bigger the amount of data, the more accurate the prediction will be.
3. **Data Preparation:** After collecting the data, this needs to be processed for further steps. Data preparation is a step where we set our data into a suitable place and qualify it for use in our machine learning training. In this step, we first ready all of the data together and then randomize the ordering of data. This step can be further divided into two processes:

   - Data exploration:
     Data exploration is used to understand the nature of data that we have to work with. We need to examine the characteristics, format, and quality of data. Better consideration of data leads to an effective outcome. In this, we discover correlations, general trends, and outliers.
   - Data preprocessing:
     At this point, the next step is the preprocessing of data for the purpose of analysis.

4. **Data Wrangling:** Data wrangling or data preprocessing is the process of cleaning and converting raw data into a useable format. It is the process

of purifying the data in order to address quality issues, selecting the variable to use, and transforming the data in the proper format in order to make it more suitable for analysis in the next step. It is one of the most vital steps of the entire process. In addition, gathered data is not necessarily always useful to the user. In real-world applications, collected data may have various issues, including:

Missing Values
Duplicate data
Invalid data
Noise

Accordingly, we use various filtering techniques to clean the data. It is mandatory to detect and remove the above issues because these can negatively affect the quality of the outcome.

5. **Model Data:** In order to gain insights from the data through machine learning, a target variable must be determined; this is the factor in which the user aims to gain a deeper understanding of. In this step, the appropriate selection of analytical techniques like classification, regression, cluster analysis, association, and building models review the result. This consists of two important processes for an AI model;
   Training Phase: In this step, we train our model to improve its performance in generating better outcomes for the problem. We use datasets to train the model using various machine learning algorithms. Training a model is required so that it can understand the various patterns, rules, and, features.
   Testing Phase: In this step, we check for the accuracy of our model by providing a test dataset parallel to it. Testing the model determines the percentage accuracy of the model as per the requirement of the project or problem.
6. **Interpret and Communicate:** One of the most difficult tasks of machine learning projects is explaining a model's outcomes to those without any data science background, particularly in highly regulated industries such as healthcare. Traditionally, machine learning has been thought of as a "black box," because it is arduous to interpret insights and communicate the value of those insights to stakeholders and regulatory bodies. The more interpretable a model is, the easier it will be to meet regulatory requirements and communicate its value to management and other major stakeholders.
7. **Implement, Document, and Maintain:** The final step is to implement, document, and maintain the data science project so that the stakeholder can continue to leverage and improve upon its models. Model deployment often poses a problem because of the amount of coding and data science experience it requires and because the time-to-implementation from the beginning of the cycle that uses traditional data science methods is prohibitively long.

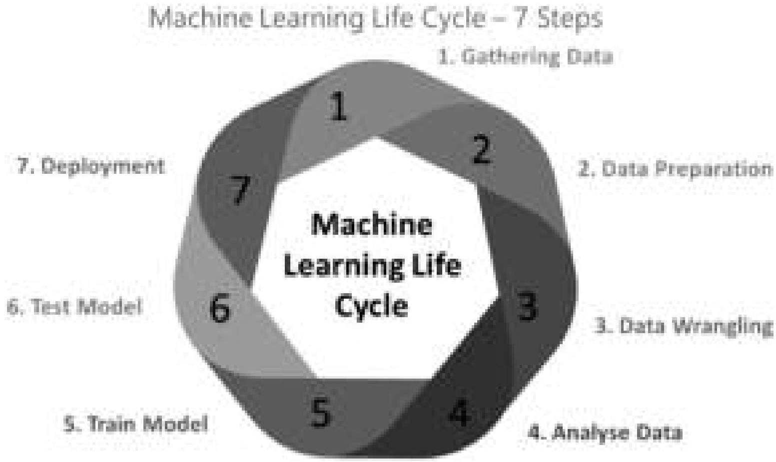

FIGURE 5.3 Lifecycle of an AI/ML Working Model [23].

5.5 PREREQUISITES FOR BUILDING AN ML/AI-BASED AGRICULTURAL MODEL

Competent expertise or knowledge of the following is required in order to pursue an ML/AI project:

Basic Computer Knowledge
Linear Algebra
Statistics and Probability
Calculus
Graph Theory
Programming Skills – Language such as Python, R, MATLAB, C + + or Octave
Data, Hardware

5.6 ADVANTAGES OF AI IN AGRICULTURE

AI has a major role in Agriculture 4.0, and the advantages are numerous. Examples of leverage with the introduction of AI in agriculture are [24]:

1. AI provides better insights into data obtained from the field and, thus, helps in the adequate utilization of resources/inputs.
2. Agricultural data is effectively analyzed by the AI models so as to make precise predictions.
3. AI reinforces the cultivation, harvesting, and marketing of crops in efficient ways.

4. The AI model makes disease detection a feasible process, hence improving the potential for healthy crop production.
5. AI technology has been the backbone of agricultural businesses in the era of Agriculture 4.0 and has significantly promoted and raised new business opportunities.
6. AI has considerably revolutionized the weather forecasting system in agriculture, and this plays a vital role in agriculture.
7. Crop management practices have reached new heights, and it has become quite convenient for farmers to manage crops with minimal effort.
8. AI has provided solutions to many challenges in agriculture including pests, weeds, etc. that have a devastating impact on the yields.
9. The introduction of AI in combination with big data has helped in curtailing the hazards on nature by applying the best possible means to reduce the exploitation of the environment.
10. A greenhouse is still one of the best practices that has value in the agricultural domain. AI mechanisms have produced results far better than manual operations in terms of maintaining that a greenhouse is working properly.

5.7 CONCLUSION

AI has been a game-changer in every aspect of the industrial world as well as in the agricultural revolution. Every day, more innovations are being discovered because of global interest and research. This chapter explained the basics of AI including the workings of some of its features and types. The use of AI in various agricultural decision-making or modeling is discussed in the succeeding chapters as well.

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6 Machine Learning (ML) Driven Agriculture

6.1 COGNITIVE TECHNOLOGIES

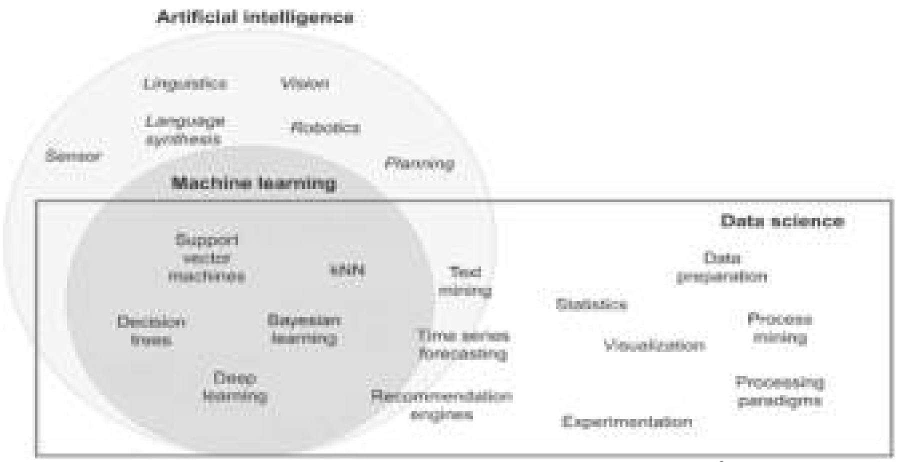
In simple terms, cognitive technology is referred to as narrow AI due to its target applications. It is usually easier to invest in cognitive technology and make a maximum profit rather than risking this for AI. Cognition characteristics have three types, and this is also known as 3 P's of cognition [1]:

1. Perceive: The perception of the cognitive technologies is the ability to understand the distinct situation it is designed for (i.e. the inputs fed to it and the environment it is surrounded with). Examples of these technologies include image and object recognition and classification (including facial recognition), natural language processing and generation, unstructured text and information processing, robotic sensor and IoT signal processing, and other forms of perceptual computing. Advancements in neural networks and deep learning have caused perception-focused capabilities of cognitive technologies to progress.
2. Predict: Prediction has also been a key application of cognitive technologies and has proven to be successful. The working principle is to understand patterns and predict the outcomes from different iterations and improve the performance by adding each outcome to experience. These technologies use various types of machine learning, big data, and statistical approaches to process, analyze, determine patterns or anomalies, and suggest succeeding steps or produce results.
3. Plan: Planning involves the inputs and learning that are gained by the machine in making decisions and strategizing future steps by mimicking human decision-making. This area of cognitive technologies has a future in machine intuition, common sense, emotional IQ, and other factors that make humans superior in planning and decision-making.

At this point, it can be concluded that cognitive technologies are a subset of artificial intelligence, with a focus on narrow AI or specific tasks [1] (Figure 6.1).

6.2 INTRODUCTION TO MACHINE LEARNING

During the 1950s, machine learning (ML) was launched as a method unique to artificial intelligence, but it shifted its momentum towards computationally achievable algorithms [2]. The science and technology of machine learning focus



focus on Narrow AI or specific task.[1]

FIGURE 6.1 AI, ML, and Data Science Techniques

and involve all of the processes that are linked in making a machine able to learn from instructions and experiences so as to improve its performance [3]. There are various concepts that may inspire certain aspects of biological learning [4–6].

The following are some of the definitions of machine learning:

> "Machine learning (ML) is the study of computer algorithms that improve automatically through experience. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as 'training data,' in order to make predictions or decisions without being explicitly programmed to do so."
>
> —Wikipedia [7]

> "Machine learning is an application of artificial intelligence (AI) that provides systems with the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use this learn for themselves."
>
> —Expert System [8]

For machines, in particular, it can be concluded that a machine "learns" when it is programmed in such a way that makes it able to change its structure so that it has a chance of improving the future results.

The possibilities of learning come from the inputs given to a machine or in response to external information and thus, the experience of the model adds to its level of accuracy. Within the scope of this book, the machine learning process can be considered as generally comprised of three main components:

I. Input: The input is the data or information that is given to the machine, such as sensor data in the case of agricultural application.
II. Machine Learning Model: A machine learning model is a model that is trained on certain training data and is then able to process additional data in order to make predictions [7]. It is the main component that performs the actual task, and the one with maximum performance quality in terms of convenience and efficiency for this particular purpose is chosen as there are a number of models/ techniques in machine learning systems.
III. Output: The output is the result that is derived from a machine learning model [9].

In general, machine learning is basically a subset of artificial intelligence that improves the performance of data analysis [10].

ML can also be defined as a technology in which an intelligent machine deduces information and knowledge from data using supervised or unsupervised learning. In supervised learning, the user plays an active role in guiding the machine to learn, while in the case of unsupervised learning, the categorization and organization of data are executed without user intervention [11].

With the rapid increase in the computing power of the machines and efficient big data handling, machine learning has reached new heights while using a set of algorithms, tools, and techniques.

The Industrial Revolution 4.0 has witnessed a growing trend of ML, including a wide range of applications, in almost every sector.

ML replicates the human learning procedure by training on the data by applying algorithmic learning and then subsequently being able to work on similar data trends. Though ML lags far behind human intelligence, there have been instances where ML has been on the dominating side depending on the nature of the task at hand.

Taking the example of traditional methods such as Excel, these are not usually able to handle a huge amount of data but this is not the case with ML, as it is designed with a purpose to become more accurate with the increase in data/ information which is fed to the algorithms [12].

6.2.1 ML in Agriculture

As previously mentioned in detail, agriculture is of global importance, particularly in a country such as India where it serves as the backbone of the economy. The growing demands for food due to the increase in population have become the primary reason for adopting new and innovative technologies in agriculture. Hence, ML is one of such disruptive technologies that have become crucial in the application of precision agriculture in achieving its goals. ML is a vital part of Agriculture 4.0 as it leverages crop yields, lowers the input cost, and minimizes “losses and risks” by predicting unfavorable conditions like rains, droughts, and similar cases.

In order for agriculture to avail of the maximum benefits from the latest technology, agriculture should survive and adapt to changes that are occurring worldwide. PA has been boosted significantly by the virtue of the knowledge shared to farmers by experts who implement ML techniques to the data derived from the agriculture and various other sources. Moreover, they infer valuable information, and the implicit predictive ability of ML models could be embedded in automatic processes such as expert systems [13]. This extraction of meaningful information from data has been the plinth for ML introduction in agriculture [14].

6.2.2 ML in WSN and IoT

In agriculture, IoT and WSN are the foundation of machine learning models. In the context of WSN, a learning model can be a simple parametric function that learned from data and a few input variables so as to leverage results. As previously discussed in Chapter 3 of this book, WSN can consist of smart, heterogeneous, cost- and energy-efficient sensor nodes that detect the physical environment [15], and transfer this data to a merging centralized unit called the base station or sink node for further processing [16], [17].

With the advancement in technologies, machine learning has proven to be an excellent option in addressing the issues of WSN by applying the same traditional data to develop networks that are more efficient and can serve as forecasting models. In terms of the implementation of ML in WSN, there is a multitude of reasons and some of them are mentioned below [2]:

I. In a dynamic environment, WSN issues are addressed by the ML which helps in the optimization of the nodes for better adaption.
II. ML provides efficient computational possibilities for complex environments.
III. With the introduction of ML in WSN, there has been a boost in precision agriculture.
IV. IoT technologies have improved significantly.

6.3 TYPES OF ML

Machine learning models work on the algorithms that are constructed with the aim of gaining a self-learning property; thus, ML is categorized as a major area of artificial intelligence. “ML algorithms” differ from “conventional computer algorithms” that work strictly according to the program created by its developer. “ML algorithms” interpret and analyze the input as well as the output (results) so that the machine learning model increases accuracy with this progression. The advantage of these methods is less dependence of the model on user instructions, unlike the conventional statistical methods [14]. The main types of machine learning are shown in Figure 6.2 below:

There are four main kinds of machine learning techniques (illustrated in Figure 6.4). These are further examined below:

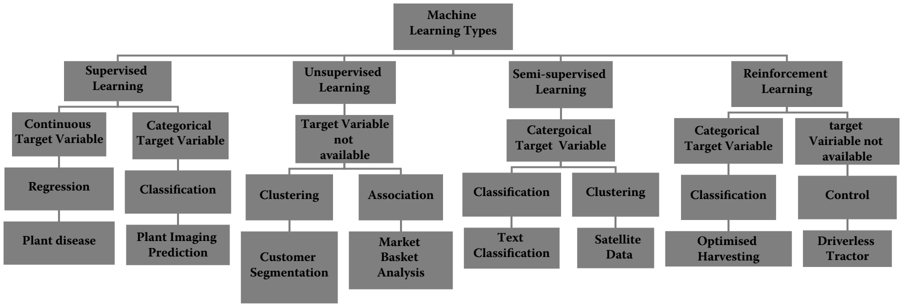


FIGURE 6.2 Machine Learning Types.

6.3.1 Supervised Learning

Supervised learning is the type of machine learning where an algorithm is provided with some training examples so that it can interpret and analyze the inputs and their corresponding outputs [14]. Supervised machine learning algorithms use labeled training datasets, and the model generates an inferred function from the relationship between output, input, and parameters of the system [2]. This type of model is ready and qualified after sufficient training and is able to work on new input. Moreover, there is a provision in modifying the model after comparing the results with the intended/correct results [8].

The following target values are present in the case of supervised learning:

a. If a "continuous target variable" is present, then it becomes the problem-case of regression.
b. If a "categorical target variable" is present, then it becomes the problem-case of classification.

Some popular supervised learning algorithms are decision trees, support vector machines, neural networks, *k*-nearest neighbor, Bayesian networks [2], linear SVC (support vector classifier), logistic regression, Naive Bayes, linear regression, support vector regression (SVR), regression trees, and more [18]. A few of these supervised machine learning algorithms are discussed below:

6.3.1.1 Decision Trees

In the case of decision trees, a predefined set of characteristics is present, and this assigns the data points of the dataset according to these characteristics, thus forming a predictive model [19].

In an easier manner, it can be inferred that decision trees work by repeating the process of learning involved in the output in order to predict the output labels [2].

6.3.1.2 Support Vector Machines (SVM)

Support vector machines are very useful in discovering the space-time correlations in the datasets by composing set hyperplanes in a feature space that separates the data by significant margins by using its algorithms. SVMs are preferred when it comes to solving nonconvex unconstrained optimization problems [2].

6.3.1.3 Neural Networks

Neural networks are currently one of the widely used ML techniques that are ambiguously inspired by a biological neural network. The simple neural network consists of three layers: an input layer, a hidden layer, and an output layer. The model consists of a number of nodes called "neurons," and the connections between neurons are called "edges" [7]. Usually, high computations are involved in the neural network model [2].

6.3.1.4 K-Nearest Neighbor (*k*-NN)

Due to the simplicity of the *k*-NN algorithm, it is the commonly used method for supervised learning. In this technique, a test sample data is classified based on the labels of nearest data samples using the "minimum-distance classification method" into the user-specified *k* value (*k* is the number of neighbors to consider) [2], [20].

6.3.1.5 Bayesian Learners

In Bayesian learners, the algorithm requires comparatively less training samples than other ML algorithms [2]. A probability distribution is used in Bayesian methods to ease the learning of uncertain labels [21], [22]. There are various types of Bayesian learners that help the model to learn the relationships better like Dynamic Bayesian Networks, Gaussian Mixture Models, Conditional Random Fields, Hidden Markov Models, and more. [2]. Bayesian networks are a type of probabilistic graphical model that uses Bayesian inference for probability computations. [23]

6.3.2 Unsupervised Learning

In unsupervised learning, the machine learning algorithm is not provided with any target variable [14], (i.e. there is no data set to which the algorithm can refer) [18]. As there are no labeled datasets or output vectors, the ML model checks for similarities in the given dataset. The unsupervised machine learning algorithm discovers the hidden relationships and patterns among the variables [2].

Algorithms involving clustering and association techniques belong to this category of ML [14].

In general, there are two types of algorithms in unsupervised machine learning [18]:

I. Clustering: This algorithm refers to the segregation or distribution of a dataset into a number of relatively small groups such that the dataset in each group/cluster is more similar to each other than to those in other groups. Data points with more similarities are grouped into a cluster and likewise, many clusters are formed.

II. Association: This type of algorithm is focused on finding certain relationships between variables in large databases.

In simpler words, we can conclude that clustering is related to the grouping of the data points according to the relatively common attributes or similarities that they possess, while association is based on the relationships between the likeness of data points and discovering patterns among the attributes of those data points [18].

Some of the unsupervised machine learning algorithms are:

Principal component analysis, *k*-means clustering, dimensionality reduction, neural networks / deep learning, singular value decomposition, independent component analysis, distribution models, and hierarchical clustering [18]. Furthermore, *k*-means clustering and principal component analysis are the most important algorithms [2].

6.3.2.1 Principal Component Analysis

Principle component analysis involves an algorithm for unsupervised learning in which the extraction of important information only, referred to as principal components, from data is performed. In actuality, principal components are a new set of orthogonal variables. Principle component analysis is suitable for data compression and dimensional reduction. Usually, in the case of big data, it simplifies the process by selecting only significant principal components and discarding other lower-order, insignificant components from the model [2].

6.3.2.2 K-Means Clustering

K-means clustering is another method that is used for the classification of the unlabeled data using clustering. Clustering is important for the machine learning process of the model and is useful in finding trends for a dataset in which the data points are fairly similar [24].

In this algorithm, the center point of the clusters is calculated, and the data points of the dataset are accumulated with the help of "minimum-distance classification" based on the similarities. In this case, ***k*** refers to the number of centroids, and "**means**" refers to the centroid [20].

6.3.3 Semi-Supervised Learning

Semi-supervised learning is considered as a combination of supervised and unsupervised learning, as both labeled and unlabeled data are used to train the ML model. Usually, the unlabeled data used in training is significantly larger than the labeled data.

The driving forces in selecting either a supervised or unsupervised machine learning algorithms are mainly the data structure, size of data to be handled, and the application scenarios [18]. According to many machine-learning researchers, the use of semi-supervised algorithms has been discovered to considerably improve the learning accuracy of a model [7].

Note: There exists another type of ML that should not be confused with "supervised learning," and it is known as "weakly supervised learning." As the cost of obtaining labeled data is usually expensive due to the fact of it being hand-labeled and not easy to obtain, inexpensive training labels that are noisy, limited, or imprecise are used, and these are able to produce a satisfactory ML model [25].

6.3.4 Reinforcement Learning

In reinforcement learning, the feedback (i.e. reward or error) for every action is reflected to the algorithm (known as the reinforcement signal [8]), and this cumulative feedback reinforces the performance and efficiency of the algorithm thus maximizing advantages with experience.

Many reinforcement learning algorithms use dynamic programming techniques [7]. Some popular algorithms are genetic algorithms, Markov decision algorithms [14], Q-learning [22], [26], etc.

Note: Explaining each algorithm in detail is beyond the scope of this book, so only precise and basic descriptions of these algorithms have been mentioned in order to make reader aware about the ML techniques used in agriculture

6.4 ARTIFICIAL NEURAL NETWORKS AND DEEP LEARNING

In the previous sections of this chapter, AI, its subsets, AI techniques, ML, subsets of ML, and ML techniques have been explained. There is a common misunderstanding that arises when relating terminologies such as artificial intelligence, machine learning, artificial neural network, and deep learning. The correlations of AI, ML, ANN, and DL have been illustrated in the stacked Venn diagram in Figure 6.3 below:

Originally, an ANN was aimed to solve problems in the same way that a human brain would [7]. One of the widely used methods in machine learning is the artificial neural networks (ANN), which tries to mimic the human brain in performing complex functions such as pattern generation, cognition, learning, and decision-making [27]. ANN helps to develop multiple relationships between clusters of information and is often preferred in cases where data points have nonlinear relationships [24]. There are broadly two categories of artificial neural networks: "traditional ANNs" and "deep ANNs."

Traditional ANNs: These ANNs are categorized into the supervised models of machine learning and are typically used for regression and classification problems [28]. The ANN model consists of a number of nodes/units called "artificial neurons" that are connected to one another to form a network, and the connection among them is called edges. Both nodes and the edges have weights that can

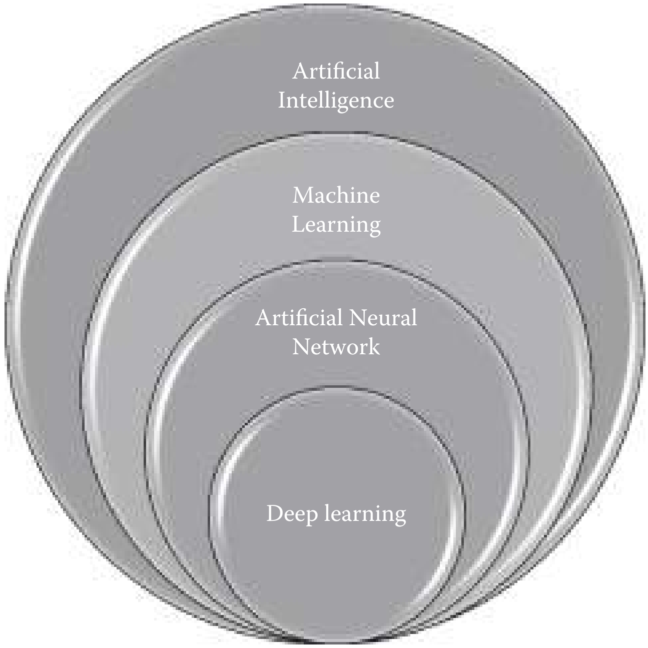


FIGURE 6.3 Subsets of AI Illustrated in a Stacked Venn Diagram

increase or decrease the strength of the signal of a connection as the learning continues [7]. In a simple ANN model, the nodes are placed in different layers: the input layer (input), one or more hidden layers (learning), and the output layer (result) [28].

> Some example of ANNs algorithms are: radial basis function networks [29], perceptron algorithms [30], back-propagation [31] and resilient back-propagation [32], counter propagation algorithms [33], adaptive-neuro fuzzy inference systems [34], autoencoder, XY-Fusion, supervised Kohonen networks [35], Hopfield networks [36], multilayer perceptron [37], self-organizing maps [38], extreme learning machines [39], generalized regression neural network [40], ensemble neural networks or ensemble averaging, self-adaptive evolutionary extreme learning machines [41], and more.

In Figure 6.4 below, a simple artificial neural network is illustrated, wherein the circles represent the "nodes" (artificial neurons), and the lines joining the artificial nodes represent the "edges."

Deep ANNs: These ANNs are also known as deep learning (DL) or deep neural networks (DNNs) [42], and the adjective "deep" in deep learning comes from the use of multiple layers in the network [43]. A DNN model is presented in Figure 6.5 below. In simple terms, DNNs are ANNs with many hidden layers, but the type of learning can be supervised, semi-supervised, or even unsupervised. Multiple levels of data abstraction are done through these various

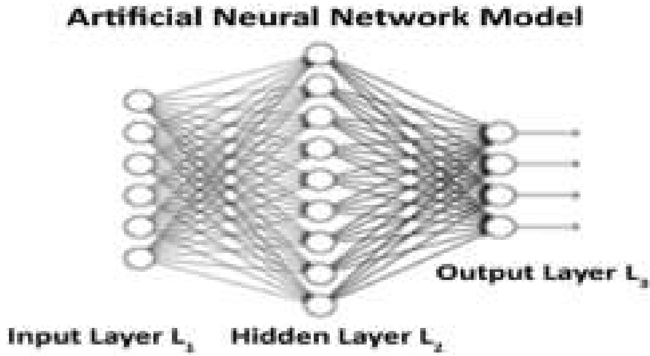


FIGURE 6.4 Simple Illustration of an Artificial Neural Network Model

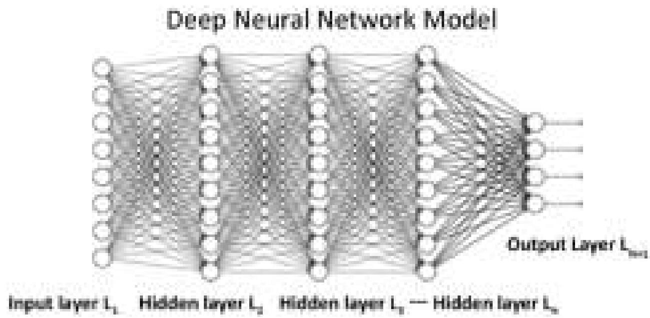


FIGURE 6.5 Simple Illustration of a Deep Neural Network Model

hidden layers, and one of the key features is that it sometimes performs the step of feature extraction itself.

> In various domains on a particular task, these models have provided results that were closer or have even surpassed human expert performance [43]. Furthermore, DL models have dramatically improved agriculture [28].

6.5 GENERAL APPLICATIONS OF MACHINE LEARNING

Some of the major applications of machine learning are identified in Figure 6.6 below:

6.6 SCOPE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN AGRICULTURE

There are many sectors in agriculture wherein AI and ML have a tremendous scope. Agricultural products, in-field farming techniques, and other related

FIGURE 6.6 Applications of Machine Learning.

processes that cast a direct or indirect impact on agriculture have been revolutionized. Some of the sectors where the scope of AI and ML are remarkable are mentioned below:

1. Agricultural IoT:
   The agricultural IoT has been explained clearly in Chapter 4 of this book, and one can deduce the importance and impact that it has on the agricultural domain. The implementation of AI and ML in IoT has augmented its performance.
2. Agricultural Data Analysis:
   The huge data that is generated requires meticulous analysis so as to gain strong insights, and AI/ML provides the best solution to these needs. Some image-based observations developed by virtue of AI/ML are useful in disease detection, crop readiness identification, field management resource optimization, and more.

3. Agronomic Products:
   The judicious use of agronomic products, like seeds, among others, is significantly improved by these technologies, as intelligent decisions are recommended to the farmer and these are all based on influencing parameters such as soil condition, weather, market trends, customized needs of a specific farmer, etc.
4. Crop Monitoring:
   One of the important aspects of smart precision farming is crop monitoring, as all other efforts are highly dependent on the effective monitoring of crops which could otherwise downgrade the general agricultural outcome. AI and ML used in technologies like hyperspectral imaging, 3D laser, remote sensing, etc. have made crop monitoring easy, convenient, and accurate.
5. Agricultural Automation:

AI and ML have made automation in agriculture possible, so agricultural practices have drastically improved as compared to the time when human efforts were heavily relied on. There are numerous areas in agriculture where AI has played a huge role in automation.

Some of the processes like irrigation required a vast experience and knowledge of farming; however, precision in this process was not manually possible. With the development of an AI/ML-based model that automates irrigation, water wastage has been notably reduced, and optimum irrigation has increased the overall yield [44].

6.7 APPLICATIONS OF AI AND ML IN AGRICULTURE

AI has proven to be one of the effective and strategic solutions for the current world scenario of fewer resources and enormous demand. To a great extent, the expectations of farmers have been met, and the key reason is an increase in productivity. In the past, one could not have imagined that AI algorithms could precisely predict and galvanize an agricultural revolution [45]. Smart farming powered by AI/ML high-precision algorithms keeps farmers at par with the technological world and has substantially contributed to the agricultural realm [44], [46]. Some of the individual applications of AI and ML are elucidated below:

6.7.1 Soil Management

Soil is a heterogeneous natural resource that is most essential in agriculture, and knowledge about soil is necessary for improving agricultural yield. There are processes involved in soil that are complex in nature as well as mechanisms that need strenuous efforts to understand. Information about available soil should be accurate in order to gain proper soil management. The data of agricultural soil properties, such as the estimation of soil drying, condition, temperature, and moisture content, etc. are fed to an ML model that produces a reliable solution for providing valuable insights. Hence, soil management becomes straightforward in order to avail maximum benefits for agricultural purposes [28].

Examples of this technology include **Trace Genomics** – machine learning for diagnosing soil defects, similar to the **Plantix app** [47]. California-based company **Trace Genomics** provides soil analysis services to farmers. Its lead investor – **Illumina** – helped develop the system which uses machine learning to provide clients with a sense of their soil's strengths and weaknesses. After submitting a sample of soil to **Trace Genomics**, users reportedly receive an in-depth summary of their soil contents [48].

6.7.2 Smart Irrigation System

AI-Powered smart automated irrigation systems are capable of providing constant precise and optimum irrigation necessary to maintain desired soil conditions. This reduces water wastage, labor costs, production costs, and increases overall yield. Many scientists believe that the judicious use of water in these irrigation systems is likely to produce a global impact on water [46].

The estimation of evapotranspiration is necessary to design and manage a smart irrigation system, but it is a complex process to accurately calculate. This problem is solved by AI and ML algorithms that precisely estimate evapotranspiration [28]. Examples of this technology include Cultyvate [49], DIGITEUM [50], etc.

6.7.3 Weather Forecasting

Agriculture is highly dependent on favorable weather conditions, and any undesired alteration has dire consequences on productivity. Weather forecasts become immensely important so as to avoid any of the issues that can cause detrimental effects. There has been massive progress in the accuracy of weather forecasting due to the implementation of the AI algorithms and hence, AI indirectly contributes to the agricultural arena [14].

Seasonal forecasting models help in improving agricultural accuracy and increasing productivity.

These models are able to predict upcoming weather patterns months ahead of time in order to assist the decisions of farmers. Seasonal forecasting is particularly valuable for small farms in developing countries such as India, which is rain-dependent. Examples of this technology are IMD, ViSeed, NEWA [51], etc.

6.7.4 Agricultural Drones

Drones have applications in various sectors, including the agricultural arena. With AI implementation in drones, its application in PA has significantly increased as it is convenient for a farmer to operate. Drones help in various operations like data collection, crop and field monitoring, disease detection, many

PA practices such as spraying inputs, surveillance, etc. Examples include Sky Squirrel Technologies Inc. – a leading company that has introduced drones for high vineyard crop yield and reduced overall cost. Algorithms integrate and analyze the captured images to provide a health report of the crops [52].

6.7.5 Agricultural Robots

The aim of AI has always been to minimize human efforts by using disruptive technology. The agriculture realm is one of the important fields of the world that needs automation and smart devices that can perform functions that traditionally needed human intervention. Companies are developing and programming autonomous robots that can handle essential agricultural tasks, such as harvesting crops at a higher volume and faster pace than human laborers [46]. Blue River Technology (John Deere) has developed a robot called ‘‘See & Spray’’ which reportedly leverages computer vision and ML to monitor and precisely spray herbicide only where needed. Another example is “RIPPA” which exterminates pests and weeds [53].

6.7.6 Tackling the Labor Challenge

Reportedly, the lack of laborers has led to millions of dollars of revenue losses in key farming regions. Examples of such efforts include, “Harvest CROO Robotics” for crop harvesting [52]. Harvest CROO Robotics developed a robot to help strawberry farmers pick and pack their crops. It claims that the robot can harvest eight acres in a single day and replace 30 human laborers. The robot grasps the leaves, inspects the plant for ripe strawberries, and then plucks the ripe ones.

6.7.7 Driverless Tractors

Combining ever-more sophisticated software with “off-the-shelf” technologies such as sensors, radars, and GPS systems, farmers will soon be able to hand this century-old machine over to robots. Examples include smart tractors that are an AI-based machine with a multitude of technologies loaded like

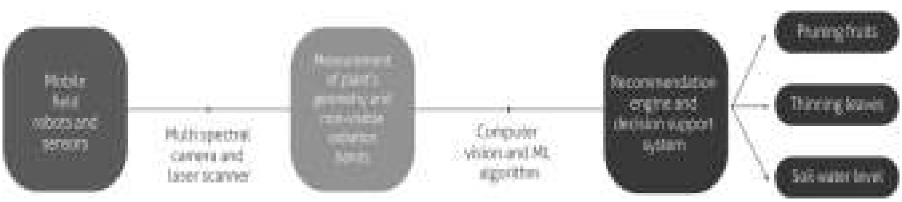


FIGURE 6.7 Blue River Technology (John Deere) [44].

sensors, radars, GPS systems in order to perform the functions without an operator.

6.7.8 Crop Sowing

Essentially, AI in crop sowing is used to drive predictive analytics in determining when and how to sow. Crops can also be sowed using AI-aided machinery at equidistant intervals and at optimal depths.

6.7.9 Crop Monitoring Systems

The introduction of AI and ML in the agricultural practices for crop monitoring has a deep positive impact on overall agriculture, as many of the aspects have been enhanced. Some of these areas are mentioned below:

I. Crop Selection and Crop Yield Prediction

   Proper selection of crops plays a key role in determining the yield, and the selection depends on various parameters like the topography of the region, climate, soil type, composition of the soil, market trends, etc. The algorithms used in AI and ML are smart enough to make multi-dimensional analyses to predict the most appropriate crop that can maximize the yield. Commonly used tools for this purpose are ANN, *k*-NN, decision trees, etc. [54–57]. Examples include the following:

   Microsoft is currently working with farmers from Andhra Pradesh to provide advisory services using the Cortana Intelligence Suite equipped with machine learning and Power BI. The pilot project uses an AI sowing app to recommend sowing date, land preparation, soil test-based fertilization, farmyard manure application, seed treatment, optimum sowing depth, and more to farmers, and this has resulted in a 30% increase in average crop yield per hectare.

   Berlin-based agricultural tech start-up PEAT has developed a deep learning application called Plantix that reportedly identifies potential defects and nutrient deficiencies in soil. An analysis is conducted by software algorithms that correlate particular foliage patterns with certain soil defects, plant pests, and diseases. This intel-powered AI program tackled the grasshopper menace for tomato crops.

II. Disease Detection

   Accurate disease prediction has been a breakthrough in smart precision agriculture. The AI and ML techniques present a high degree of accuracy in comparison to the traditional statistical approaches, as AI/ML models have been able to analyze heterogeneous and data with noise better [58–60] and, therefore, input is specifically targeted in terms of time, place, and affected plants [46].

   The SVM technique was initially used for disease detection and classification [61]. Other examples include the algorithms of ML that are used for pattern recognition in detecting diseases by using images of the crop leaves [14], [62].

III. Weed Detection
Elimination of weeds from the field was traditionally done by sacrificing the environment. However, an alternative solution from computer vision and ML algorithms improved weed detection and used an AI-based machine to destroy this without degrading the environment by herbicide application [46].

IV. Crop Quality Improvement

AI and ML help in finding new possibilities to improve every step taken in agriculture. This is also paving way for improving crop quality. Human limitations in analyzing the data and forming relations among various influencing parameters can be an example of a limitation, while an AI-powered machine can use this information to recommend a method to improve the crop quality [46].

6.7.10 Deciding the Minimum Support Price (MSP)

Typically, the MSP is the responsibility of the government in order to provide security to farmers, and this MSP varies from crop to crop. It is the minimum price that a crop will reap. In order to decide the MSP, there are numerous factors that influence this – specifically, total expenses in growing the crop, fluctuations in input costs, demand and supply, market price trends, inter-crop price parity, area-specific costs like transportation, marketing costs, etc. [63]. This complex, big data formed from these factors need a rigorous analysis which conventional methods usually fail to perform. Hence, the techniques of ML are best suited and able to provide notably valuable insights and a basis for deciding the MSP [14].

6.7.11 Precision Agriculture to Agriculture 5.0

AI and ML have been an absolute driving force for the paradigm shift of "precision agriculture" into "Agriculture 5.0." Real-time data, in combination with readily available data, provided to an AI or ML model produces many precise decisions for each specific purpose. In some particular tasks, these smart machines that are powered by AI were able to outperform a human expert. Such examples include the use of computer vision in image analysis. Some benefits of AI in PA include optimized and precise use of pesticides, insecticides, and other inputs, as well as the reduction in environmental degradation and overall cost reduction [46].

6.7.12 Greenhouse

AI has a very important application in greenhouse functioning. The AI-backed system designed to control and manage the climate of a greenhouse emphasizes rigorous analysis of data to achieve high precision. Due to various parameters that

TABLE 6.1
Some Smart Precision Farming Requirements and Providers

Application	Company
Soil Analysis and Monitoring	CropIn, Bengaluru
Image Analysis	Intello Labs, Bengaluru
Predictive Analysis	Microsoft, India
Supply Chain Management	Gobasco, Lucknow
Crop Cycle Expertise	Gramophone, Indore
Farm Produce Aggregation	Jivabhumi, Bengaluru
Farmer Advisory	Agrostar, Pune

need to be considered while adjusting the climate of a greenhouse, it becomes a tedious task to handle conventionally. Artificial neural networks (ANNs) and fuzzy logic controllers (FLCs) are some of the methods used in this process in attaining high accuracy in terms of regulating temperature and humidity [46].

6.8 CONCLUSION

The world has been reshaped by the implementation of disruptive technologies like AI, IoT, edge/fog, blockchain, etc. in various sectors, and agriculture is no different. ML (machine learning) is a subset of AI that is used to train machines to learn from instructions and experiences so as to improve their performance. ML has contributed significantly through intelligent automatic devices and predictive models that use precise ML algorithms to improve various agricultural practices. These predictive models are important in order to avoid any of the issues that may cause detrimental effects. ML has enormous applications in agriculture that have improved crop quantity and quality, field monitoring, management, etc. ML that is applied to agricultural big data that is used in a meticulous analysis that provides meaningful insights in making agriculture sustainable. AI and ML have been an absolute driving force for the paradigm shift of “precision agriculture” to “Agriculture 5.0.” ML has provided opportunities to enhance various steps in agriculture and thus, has a tremendous scope.

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7 Data-Driven Smart Farming

7.1 INTRODUCTION

We dwell in a rapidly growing global village that is connected in a digital world. The technological developments from the past decades have resulted in the inclusion of technology in every aspect of human life; thus, an enormous generation of multimedia, text, or numeric data occurs every day. This type of heterogeneous data from multiple sources and platforms contributes to what we call horticultural big data [1], [2]. Big agricultural data is characterized by high volume, variety, variability, velocity, and veracity which requires a specific analytical approach and technology to transform data into solutions that are ready to use in agriculture. The use of new developing technologies and hi-tech instrumentation in lieu of traditional agricultural practices is also swiftly growing. The popularity of the utilization of information and communication technologies (ICT) like cloud computing, IoT, drones, UAVs, robots, satellite and remote sensing, and sensors in the world of farming has powered a new era of the data-intensive paradigm of smart farming [3–5]. Smart farming is an advancement that emphasizes the use of information and communication technology in the cyber-physical farm management cycle. The collection of data, analysis, usage in terms of supporting decisions for smallholders, and management and sharing has profiled so-called smart farming into a practice that is leveraged and operated by data. The planning and monitoring of each task concerning irrigation, weather, fertilizer, or chemical spray and harvesting and storing all of this information to make better decisions in the future have itself led to a mammoth amount of data for each second of the task. Data-driven precision agriculture is the use of big data in supplementing on-farm precision agriculture — meaning having the right farm data at the right time in order to make better decisions to improve long-term profitability. This provides farmers, ranchers, and producers with key decision points using various data, such as planning, pre-planting and planting, in-season, and harvest data in a more interactive and meaningful way [6–8].

Big data is expected to cause changes to both the scope and the organization of farming. The agribusiness strategies and stakeholders have shifted their focus to new algorithm development, reinventing new solutions to win farmer confidence [2]. Application of big data is driven by the need for new technologies to achieve certain goals (pull factors) and thrust of new technologies in enabling people and organizations to achieve higher or new goals (Push Factors) [9], [10] (Figure 7.1) (Table 7.1).

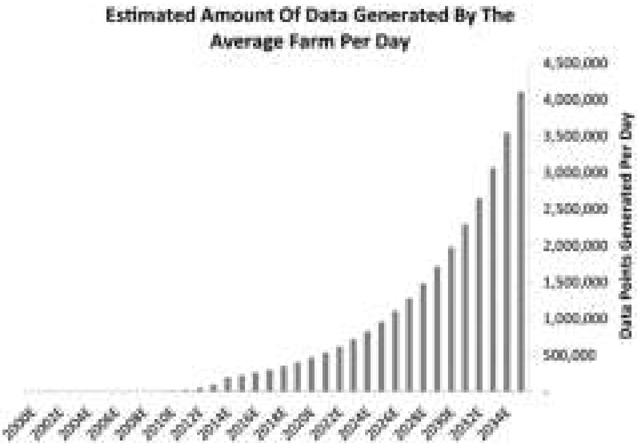

FIGURE 7.1 Estimated Data Generation by Average Farm/Day [11].

To intensify the adoption of data-driven agricultural systems for increased productivity, including providing strategic direction, data availability, improvement of precision agriculture efforts along with its global adoption in private and public sector, data-driven agriculture is currently being added to the Open Government National Action Plan 3.0 as part of the Global Open Data for Agriculture and Nutrition (GODAN) [12] initiative in the US. Big data-based smart agriculture is a major tool in the sustainable handling and managing of threats, challenges, and risks in the context of climate change, diseases, and pest attacks. Therefore, it is necessary to clearly understand the proper use of big data management tools and techniques to address the challenges of crop cultivation and animal and farming management.

7.2 COLLECTION AND MANAGEMENT OF REAL-TIME AGRICULTURAL BIG DATA

Data is a prospective tool for making decisions on the basis of an analysis of relevant situations. The use of data in driving the farming practices in a sustainable manner is now the focus of researchers, so the maximum output is produced from a small, arable piece of land [13]. A significant amount of data is created instinctively in the agricultural process during different stages ranging from seed sowing to harvesting. The collection and monitoring of real-time agricultural data are mostly automated with the use of drones, sensors, satellites, smartphones, scientific instruments, UAVs, and this is referred to as “crowdsource” [14], [15].

Companies like John Deere, Dow, and Monsanto are using data analytic techniques to develop tools and technology that are capable of making the right decisions at the right time as well as following a scientific procedure with the help of data [16]. Data should be collected from many sources and for each specific farming process. Data generated by the farming process can differ in the

TABLE 7.1
Summary of Push and Pull Factors that Drive the Development of Big Data and Smart Farming [10]

Push Factors	Pull Factors
• **General technological developments** • Internet of Things and data-driven technologies • Precision agriculture • Rise of ag-tech companies	• **Business drivers** • Efficiency increase by lower cost price or better market price • Improved management control and decision-making • Better local-specific management support • Better coping with legislation and paperwork • Dealing with volatility in weather conditions
• **Sophisticated technology** • Global navigation satellite systems • Satellite imaging • Advanced (remote) sensing • Robots • Unmanned aerial vehicles (UAVs)	• **Public drivers** • Food and nutrition security • Food safety • Sustainability
• **Data generation and storage** • Process-, machine-, and human-generated • Interpretation of unstructured data • Advanced data analytics	• **General need for more and better information**
• **Digital connectivity** • Increased availability to agricultural practitioners • Computational power increase	
• **Innovation possibilities** • Open farm management systems with specific apps • Remote/computer-aided advice and decisions • Regionally pooled data for scientific research and advice • Online farmer shops	

type, amount, and source [17], [18]. The type of data collected from the farm includes information on planting, spraying, materials, soil-related data, intercultural management-related data, climate-related data, long-term census data, harvesting data, cropping pattern data, agribusiness data yields, in-season imagery, soil types, weather, and other practices. In general, there are three categories of data generation [6], [19]:

(i) process-mediated (PM),
(ii) machine-generated (MG), and
(iii) human-sourced (HS).

PM data is the traditional business data that results from marketing, purchase, profit, and investments done on a particular agricultural task. It is rather structured data and includes transactions and reference tables. This data is stored and processed using relational databases or a business information system.

MG data is boosted from the site-specific management sensors, agricultural machines, IoT, GPS, smartphones, etc. This type of data ranges from simple, digital numerical data to highly complex multimedia data like videos, images, and maps with high volume and variety. With the use of modern technology and instrumentation in farming, this data is increasing day by day and sophisticated storage systems, databases, web servers, web-based APIs, and application software are employed to manage, process, and analyze this.

HM data comprises data that is related to human experiences and expert opinions, that are recorded in books and works of art, and later in photographs, audio, and video. Moreover, this information is now digitized into refined knowledge management systems. Census and social network data also play a vital role in recording or sharing the information [19], [20]. Government agencies have come up with many dedicated organizations that openly share datasets for the use of public research [21]. FAO developed a system entitled to Agricultural Metadata Element Set (AgMES) to handle the huge agricultural phenotypic and genomic data related to plant growth, diseases and pest resistance, and high yield features that are necessary for developing the ideal variety [22], [23]. Big Data Coalition, Open Agriculture Data Alliance (OADA), AgGateway, public institutions like the USDA, the AgriPrice Book developed by North America Strategic Institute, and Citizen Science developed by CGIAR [24] for promoting climate change and food security management are examples of other initiatives. ICAR has pioneered the initiative to start automating and digitizing agriculture by spearheading collaborations with IITs, CDAC, NBSSLUP, CRIDA, IASRI, IARI, state departments, CIAE, CSWCRI, IISS, and NRSA warehousing and development of digital databases called data lakes (centralized repository), HDFS and interpolation of the data on a real-time basis using data analytics tools and techniques like ML, Data Mining, Statistical software's [25].

The whole process from data capture to decision-making and data marketing [20] is referred to as a data chain. Figure 7.2 presents all of the farming activities for which data has to be managed for farm management below: data applications in smart farming, activities, and the key issues corresponding to each stage of the big data chain. With US$64.5 billion investments in venture capital funds technology start-ups in 2015, a total of 7% of this was earmarked in agriculture-related start-ups [26], [27] (Table 7.2).

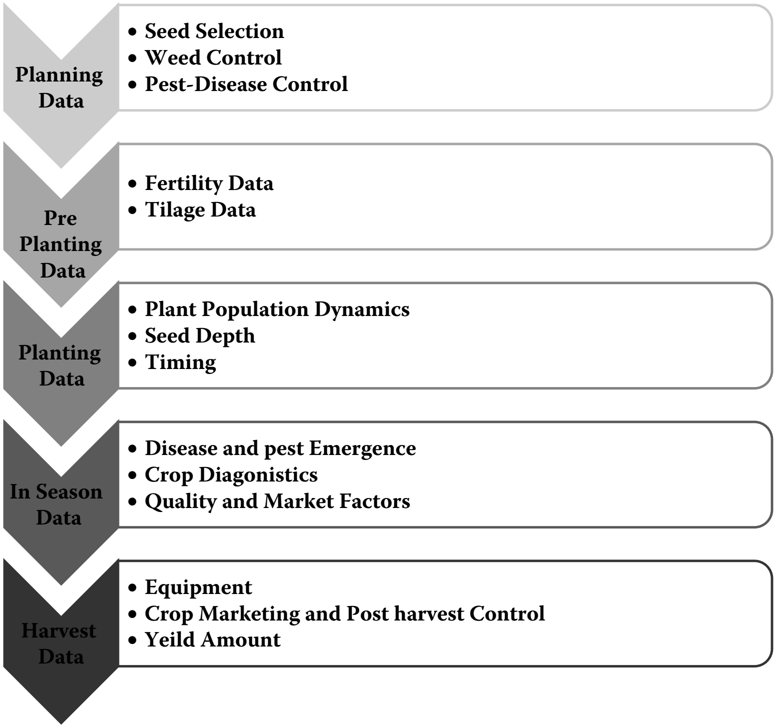

FIGURE 7.2 Data Management Required for Various Tasks.

7.3 TRANSFORMING FIELD DATA INTO MEANINGFUL INSIGHTS

After the collection of pertinent data, the most important task is to draw meaningful insights from it. Finding the appropriate methods and tools that suit the data format and mines the data deeply, intelligently, and efficiently is an unquestionably crucial step. Different software and computer programming languages and tools have been developed to interrogate data. Languages like Python, R, Scala, etc., and sophisticated software tools like SPSS, Rapid Miner, and Weka have significantly helped in statistical and predictive analyses [31]. When the results are marked out, decisions can be made accurately [32], [33]. A series of operations is carried out before generating decisions, as illustrated in Figure 7.3. The presence of data from multiple sources is managed according to its format and size in data warehouses, local databases, or cloud servers. However, it is possible to gather data that is corrupt, incompatible, or has missing values (i.e. data-rich, information-poor (DRIP) can occur, but appropriate cleaning and data preprocessing techniques are used to filter the necessary data [34], [35]. In the data analysis stage, caution should be practiced when data originate from multiple sources and are of different formats. Data fusion can be

TABLE 7.2
State-of-the-Art Big Data Applications in Smart Farming and Key Issues

Stages of the Data Chain	State-of-the-Art Big Data Applications	Key Issues
Data capture	Sensors, open data, data captured by UAVs, biometric sensing, genotype information, reciprocal data	Availability, quality, formats
Data storage	Cloud-based platform [28], Hadoop Distributed File System (HDFS), hybrid storage systems, cloud-based data warehouse [29]	Quick and safe access to data, costs
Data transfer	Wireless, cloud-based platform, linked open data [30]	Safety, agreements on responsibilities and liabilities
Data transformation	Machine learning algorithms normalize, visualize, anonymize	Heterogeneity of data sources, automation of data cleansing and preparation
Data analytics	Yield models, planting instructions, benchmarking, decision ontologies, cognitive computing	Semantic heterogeneity, real-time analytics, scalability
Data marketing	Data visualization	Ownership, privacy, new business models

defined as a combination of data attained from a plethora of sources (e.g. IoT, social networks sensors, etc.) in different formats [36]. These big data streams are mined to arrive at mean worthwhile and suggestive conclusions to initiate smart actions. Data fusion techniques have been advantageous and serviceable in robotics, complex machinery management, safety and operations, crop monitoring, and remote sensing. Data fusion can come in the form of either raw data fusion (source data), feature-level data fusion (based on important and effective features), or decision-level data fusion (interrelations and patterns in data for decision-making). The combination of data obtained by multisensory networks with a data fusion framework enables faster and lower-cost processing, in addition to reducing the level of uncertainty and hence, guaranteeing higher reliability. These data can be fused in a variety of ways – for instance, algorithms of high-level fusion techniques include the Bayesian theory, fuzzy logic, artificial neural networks, Excel, etc. [37], [38]. Certain fusion methods made in precision farming like Radar and optical data raw sensor data, [39] remote sensor and GIS data fusion, spatial data from GPS [40], UAVs [41] and temporal data from sensors, [42] and many more have surfaced. For every case of crop and disease, spectral or fluorescence imaging techniques are available to produce user-friendly information and automate infection assessment by employing data

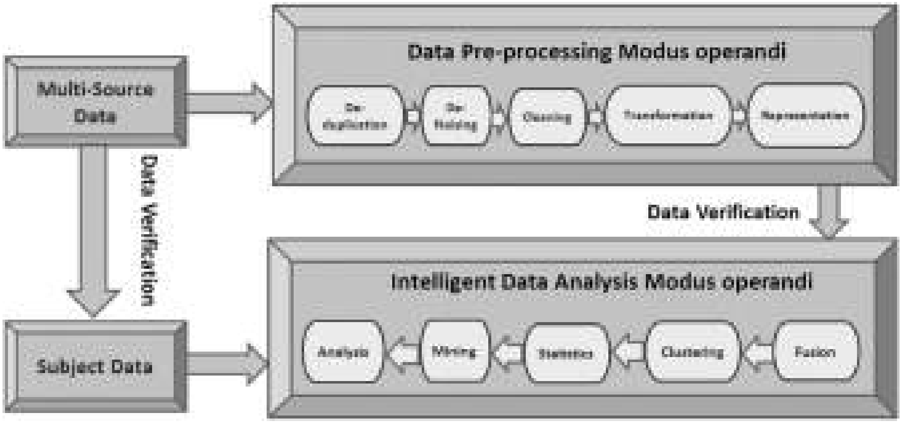

FIGURE 7.3 The flowchart of intelligent processing of agricultural big data [43].

mining and clustering algorithms like ANNs, machine learning, or other AI techniques, as previously discussed in detail in Chapter 5.

7.4 PROCESSING AND PREDICTIVE ANALYSIS OF AGRICULTURAL DATA

Growing food scarcity has led to the development of ingenious and transformational solutions for the incorporation of eco-friendly scientific tools and farming machinery. The collected big data can be applied in creating easy-to-use and accurate forecasting models to ensure that crop production is at its fullest potential. A process called predictive analysis extracts trends and forecasting insights from the data. Indeed, the traditional modeling approach was very limited; a program and input were given to a computer to merely produce an output. For example, a program for the addition of two numbers will produce a sum of the numbers as output.

Predictive analytics embody a diverse set of statistical procedures from data mining, predictive modeling, and machine learning. These analyze current and historical facts to make predictions regarding future or other unknown events by using the data [44]. The goal is to go beyond knowing what has happened in the past to providing the best assessment of what will happen in the future, along with extract trends and insights [45]. Growing volumes of data, types, as well as the curiosity to learn more from data, have impelled more and more organizations towards predictive analytics as a means to increase their bottom line and competitive advantage. Faster and more affordable computing machines and GUI-based software has driven predictive analysis to flourish beyond the community of mathematicians and statisticians. Predictive analysis is used in actuarial science, marketing [46], banking and financial services [47], insurance, telecommunications, retail [48], travel, mobility, healthcare, child protection, pharmaceuticals, capacity planning, social networking, manufacturing, and agricultural sciences [49].

The core principle of predictive analytics relies on finding the affinity between explanatory and individual variables and predicted variables from past occurrences and subsequently using them to predict the unknown outcome [50], [51]. Data analysis has a high level of granularity, detail, and, thus, high accuracy. The feature of granularity distinguishes predictive analysis from forecasting [52].

7.4.1 Predictive Analysis Life Cycle and Types

Predictive models use past experiences to develop and train a model that can be used to forecast outcomes for different data. The modeled results, in the form of predictions, represent a probability of the target variable based on estimation and the relationships from a set of input variables. Table 7.3 lists the processes that occur in the life cycle of PA below. The processes happening in PA vary from descriptive, prescriptive, and decision-modeling [53] (Table 7.3).

Presently, predictive analysis has become a new business trend for most organizations. New methods and techniques are proposed to handle the voluminous and varied datasets [54], [55]. The approaches and strategies used to conduct predictive analytics are an arsenal and can generally be grouped into traditional techniques, statistical techniques, regression techniques, classification techniques, and machine learning techniques, as described below:

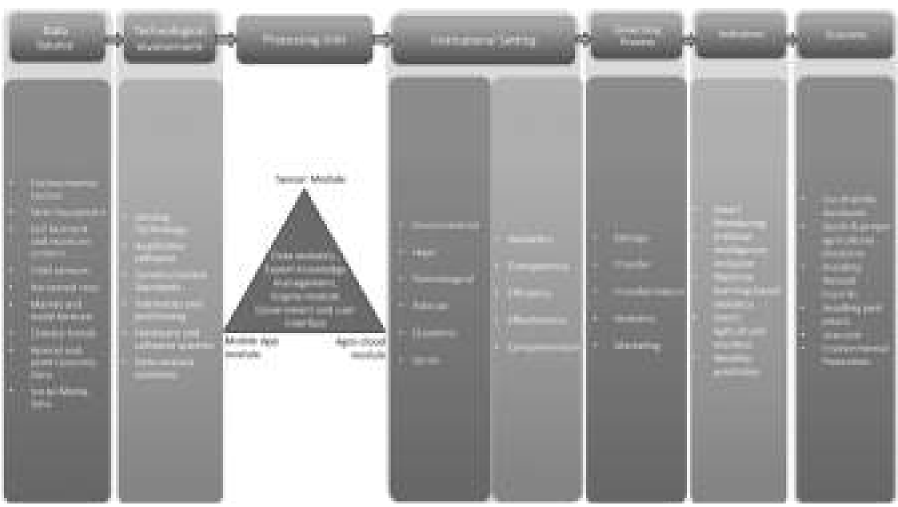

FIGURE 7.4 A Conceptual Model of Big Data-Driven Smart Agriculture for Sustainable Agriculture [9].

TABLE 7.3
Life Cycle of Predictive Analytics

Process	Action and Requirements
Project Definition	Scope, objectives, and deliverables of the project
Data Collection	Collection of data from different sources, identifying data sets
Data Analysis	Data cleaning, imputation, and modeling data with the aim of mining out important information and arriving at a conclusion
Statistical Analysis	Statistical test to check and validate hypothesis, uses standard statistical models.
Predictive Modeling	Automated predictive models for future, best optimal solution, evaluation
Deployment	Predictive model deployment, deploy the analytical results into daily task decision-making process, output can be reports and automated action, GUI software development
Model Maintenance	Model management, model performance check for reliable results

7.4.1.1 Traditional Approach

The traditional approach is a restricted option that uses historical data and experiences for the forecasting. Human experts and static models or mathematical equations are the only tools used in this approach. This approach is prone to errors, inaccurate, unreliable, and is not dynamic. These methods include many time series forecasting techniques and others that are severely limited when applied to complex systems: exponential smoothing, moving average, Bayesian networks, trend models, segmentation, regression, cross-sectional forecasting, extrapolation, queuing theory analysis, etc. This is a deterministic approach. Traditional weather forecasting methods use numeric weather prediction (NWP), a mathematical modeling based on Bayesian probabilistic arguments, which has historically led to accurate weather approximations.

7.4.1.2 Statistical Approach

Statistical techniques in predictive analytics modeling can range all the way from simple, classic mathematical equations to complex deep machine learning processes operating on sophisticated neural networks. Multiple linear regression is the most commonly used simple statistical method [56]. A statistical model is usually specified as a mathematical relationship between one or more random variables and other non-random variables. As such, a statistical model is labeled as "a formal representation of a theory" [57]. All statistical hypothesis tests as well as statistical estimators are derived via statistical models. Customarily, statistical models are part of the foundation of statistical inference. This is a non-deterministic approach. Finally, this technique forms the foundation for other approaches [58], [59].

7.4.1.3 Data Mining Approach

The prediction of future trends for agricultural tasks based on analysis of huge text, numeric, or multimedia data and the extraction of important information is referred to as data mining (DM). Data mining is known as knowledge discovery in a database, and it can retrieve meaningful data/inferences/knowledge from a large amount of the data [50]. All of the abovementioned life cycle stages as discussed in Table 7.3 are followed in this approach as well. Various techniques are used to mine data from drones, IoT, sensors, etc. Some of the popular DM methods are clustering (k-means clustering used for simulating daily precipitations and other weather variables of agriculture.) and distance measure (Euclidean distance) [60], [61].

7.4.1.4 Classification and Regression Techniques

Models or algorithms that divide data into subsets are defined by the categories of input variables. The model is prepared using training data to predict the target value. Important terms used in classification techniques include the following:

- **Classifier:** an algorithm that maps the input data to a specific target value
- **Classification model:** draws a conclusion from the input values data given for training; predicts the output labels/categories for the new data or test data
- **Feature:** individual measurable characteristics of a phenomenon being observed; principal component analysis techniques can be used to choose features
- **Binary classification:** classification tasks with two possible outcomes, 0 or 1; for example, **gender classification (Male / Female)**
- **Multi-class classification:** classification with more than two classes; in multi-class classification, each sample is assigned to one and only one target label; for example, **fruit can be ripe or unripe**
- **Multi-label classification:** a classification task where each sample is mapped to a set of target labels (more than one class); for example, **a crop can have fungal infection on both its fruit and leaves**

Regression models are the mainstay of predictive analytics. The aim is to establish a mathematical equation as a model to interpret the relations among the different variables in consideration into continuous real values. Regression analysis is used to model the relationship between a dependent variable and one or more independent variables. The vital terminology used in regression techniques are:

- **Outliers**

A reading or a value in a dataset that is either very high or very low as compared to others present in the data. In other words, when it does not belong to the population, then such an observation is called an outlier. Outliers need to be removed to produce acceptable results.

- **Multicollinearity**

When the independent variables are highly correlated with one another, then the variables are said to be multicollinear. Many regression techniques are incompatible with multicollinearity, as this causes problems in ranking variables based on their importance. Conversely, it is problematic in selecting the most important independent variable (factor).

- **Heteroscedasticity**

Heteroscedasticity is when an independent variable's variability is not equal across values of the dependent variable.

- **Underfitting and Overfitting**

When we use unnecessary explanatory variables, then this might lead to overfitting. Overfitting means that our algorithm works sufficiently on the training set but is unable to perform better on the test sets. This is also known as the problem of high variance. When an algorithm works quite poorly that it is unable to fit even a training set properly, then it is said to underfit the data. This is also known as the problem of high bias. Gradient boosting techniques are used for such anomalies.

There are a wide variety of models that can be applied while performing predictive analytics. A few of them are mentioned in the table below.

7.4.1.5 AI- and ML-Based Approach

Machine learning is a branch of artificial intelligence that was employed to build techniques to enable computers to learn. Advanced statistical methods for regression and classification form the important pillar of these techniques. Both unknown and known events are predicted from complex relationships in data. [62]. Ensemble modeling is a usual approach where many of the previously discussed techniques above are combined for better results and accuracy. In the table, various techniques are identified in addition to regression and classification. Text analytics related to precision farming on forecasting websites and social websites like Twitter, Facebook are used to mine opinions, emotions, and attitudes towards a specific aspect of the agricultural sector – such as crop production, government policies, climate changes, and beyond – have been possible as a result of build-in tools like Hootsuite insights, Quick Search, NCSU Tweet Visualizer, MeaningCloud, Sentiment Analyzer, SentiStrength, and Sentigem. Furthermore, "bag-of-words" or the hashtags and buzzwords are used to monitor behavior (Table 7.4).

TABLE 7.4
Some Commonly Used Predictive Analytical Techniques

Classification Techniques	Regression Techniques	Machine Learning
• **Linear Classifiers**	• Linear regression	• Geospatial predictive modeling
o Logistic regression	• Logistic regression	• Neural networks
o Naïve Bayes classifier	• Polynomial regression	• Deep learning
o Fisher's linear discriminant	• Stepwise regression	• Support vector machines
• **Support vector machines**	• Stepwise regression	• Multilayer perceptron (MLP)
o Least squares support vector machines	• Ridge regression	• Radial basis function
• **Quadratic classifiers**	• Lasso regression	• *k*-means
• **Kernel estimation**	• ElasticNet regression	• Apriori
o *K*-nearest neighbor		• Hidden Markov Model
• **Decision trees**		• Fuzzy C- means
Random forests		• Sentiment analysis or opinion mining (for text)
• **Neural networks**		• Dubbed polarity analysis (for text)
• **Learning vector quantization**		• Natural language processing

7.5 PREDICTIVE MODELING

Predictive modeling (PM) is the process of utilizing data and statistics to forecast outcomes with data models. These models can be used to predict anything from sports outcomes, agricultural forecasts, and business predictions. Predictive modeling is also often referred to as:

Predictive analytics
Predictive analysis
Machine learning

Each predictive analytics model can utilize more than one classifier, many predictors, or variables, that will affect the probability of various results. Before initiating a predictive modeling process, it is imperative to identify the objectives, scope of the project, expected outcomes, and datasets to be used. There are two classes of predictive models: parametric and non-parametric. Moreover, semi-parametric models also exist, and these constitute features of both. Parametric models make "specific assumptions within the finite parameter distribution." Non-parametric models "typically involve parameters for prediction belonging to infinite distribution sets and are not confined to a normal distribution, as they rely on continuous data" [63–65]. PM is as common as

TABLE 7.5
Application-Specific Use of Analytical Techniques

Agricultural Task	Analytic Techniques or Software
Weather forecasting and irrigation monitoring	Regression (both linear and nonlinear), time series (moving average, autoregression, autoregression moving average (ARIMA) [66], [67], Deep Thunder
Diseases and variety classification	Artificial neural network, deep learning, classification techniques, LettuceBot
GIS using satellite images, drone pictures, or thermography	Deep learning, ArcGis, Computer Vision, AgriBigCAT [12], [68]
Text mining from social platforms (Tweets, Facebook)	Natural language processing, deep learning [69–71]

predictive analytics in the areas of precision agriculture, finance, traffic control, fraud detection, weather forecast, and beyond [31] (Table 7.5).

7.6 CONCLUSION

Identifying and understanding the key drivers of change in data generated from a farm has led to the growth of strategic development in farming practices. An increase in food production, as well as revenue from data analytics, is itself now a new policy introduced by the government in India [72]. The current challenges are the aggregation of data and the cost incurred on the farmers from this practice. Collaboration – specifically sharing a variety of data (sensor, streamed, historical) – among producers, suppliers, processors, distributors, and the government is essential [73]. Farmers must be enthusiastic about the use of data-collecting approaches and learn about the financial benefits of these new systems. The pressure on the farmer should be reduced by multinational companies and the government by sponsoring these tools and technique implementation. Companies such as John Deere, Monsanto, and DuPont Pioneer are leading the revolution in precision farming techniques. Tractors can now autonomously plant seeds, and both John Deere and Pioneer offer variable-rate seeding, therefore, newer and more interesting practices yet in store for farmers. A number of start-ups have entered the game in an attempt to diversify [74]. Lastly, engineers, practitioners, and researchers can scrutinize future development directions and innovate. As described above, supporting agents such as robots, sensors, and humans are catering to the complex task of PA, although it faces several challenges, as presented in Table 7.6 below:

TABLE 7.6
Challenges in Precision Agriculture with Various Tools and Techniques [75]

Precision Agriculture Task	Tools and Techniques	Challenges
Planting and harvesting	Humans, robots, sensors team, and swarms' robots	Collaboration among agents in a system for given tasks
Monitoring stresses and inspecting diseases in crops	Algorithm and protocol for humans, robots, sensors teams; best matching protocols	Multiple agent collaboration; errors prevention and conflicts resolution
Forecasting yield and estimating risk by cloud computing services	Demand and capacity sharing protocols	Cloud communication for collaborative control decision support system
Measuring output and control	Advanced analytics tools	Collaborative machine learning

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8 Decision-Making and Decision-Support Systems

8.1 INTRODUCTION

Automated machines, tools, and other intelligent techniques in support of farmers for production and management, digital agriculture has flourished vigorously. Terms like "smart" and "intelligent" were prefixed to concepts and tools in order to show a new paradigm of farming. With massive information coming from multiple sources, herein referred to as horticultural big data, learning to manipulate and investigate deeper into data to produce smart and realistic solutions and decisions on the part of farmers commenced at the onset of the Green Revolution to the present age of farming called Agriculture 4.0. Decision-making itself is a new science, and much more is yet to be explored. In decision sciences, new standards in dealing with highly complex and profound information are underway. The process of decision-making is based on elements that answer the four "W" questions: Who? (individual or collective), What? (strategical, tactical, or operational), When? (proactive or provoked), and How? (information-based or intuitive) [1]. Decision support is, thus, a core concern of smart farming, and this chapter further expounds on this topic [2]. The process of decision-making is coalesced in past experiences, observed data, and analyses of the present situation. Decisions are quantitatively or qualitatively made, or both. A more complex decision-making process may require a significant amount of good judgments and quantitative analysis [3]. It is challenging to transfer variable and voluminous data and information into practical actions; therefore, platforms like decision support systems (DSSs) are requisite for making precise and evidence- and need-based decisions [4]. A formal definition of a "system" is finely provided by Wright: [5] "a system is a recognizable, composite dynamic entity made up of various discernible subsystems which are related to one another and, as a whole, are capable to perform different tasks in response to external inputs in a stable and adaptive way." Different authors have formed different descriptions for a DSS. A few [6] defined a decision support system as a data processing and distinguishing process that is based on models with the goal of increasing the quality of decisions made by decision-makers. Jones *et al.* [7] defined DSS as "a computerized system for improved quality decision-making related to partly structured issues." Sheng and Zhang [8] described a DSS as "a human-computer system capable of collecting, processing, and providing knowledge based on computers." Terribile *et al.* [9] explained a DSS as "a smart system which is able to provide feasible solutions and decision-making support related to particular issues for which data is collected." Based on the descriptions above, a DSS is referred to as a collection of tools, data, and techniques that are formed as interactive software and trained to aid in specific decision-making in real-time, depending on the type of problem [10]. DSS may range from a simple data processing tool or a complex computer-based expert system that extracts beneficial information from data, documents, or other compatible sources [11] (Figure 8.1).

The history of DSSs dates back to 1960 [12], and a breakthrough was achieved in 1967 care of Michael S. Scott Morton from Harvard University, who developed the first Model-Driven DSS to be used in marketing and finance management. In 1962, Forrester developed the first computer-based, data-driven DSS named SAGE (Semi-Automatic Ground Environment) air defense system for North America.

A productive DSS is characterized by the ease of use, ability to make on-the-spot decisions as required, and intelligible display of information in the form of graphs, reports, SMS, and smart action, among others. Reliability, adaptability to changing environments, flexibility, and accuracy are some important and resilient features of a stable DSS.

The general intentions for setting up a decision support system are [10]:

1. Ameliorating the efficiency and effectiveness of decision-makers
2. Acting as a decision-support tool for problems
3. Assisting decision-makers in managing knowledge
4. Streamlining the problem-solving process

Depending on the type of input on which a DSS works, five types of DSSs have been cataloged so far [12]–[14]:

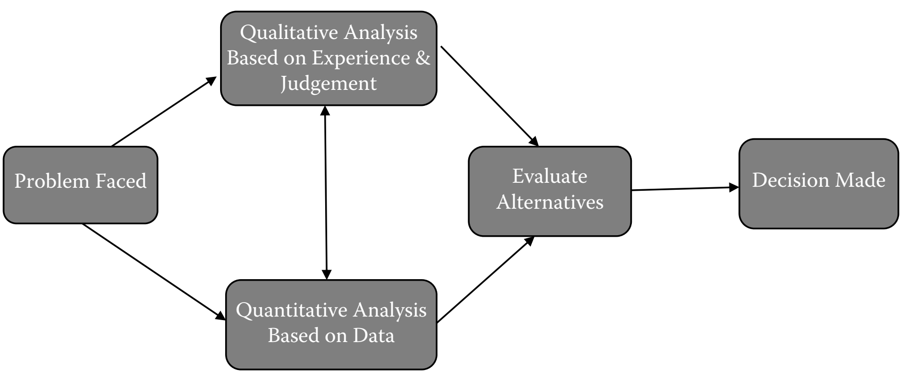

FIGURE 8.1 Overview of the Decision-Making Process [3].

1. Communication-Driven
   Communication-driven DSS is also called group decision support systems (GDSS). It includes more than one person working in coordination to solve a complex problem. An example of this is online chat rooms or meeting platforms like Webex, Zoom, and other instant messaging software.
2. Data-Driven
   Data-driven DSS are support systems impelled by a huge amount of real-time or offline data feeding and high-end ML/AI-based data analytics for the generation of decisions. These systems work on huge databases and data lakes.
3. Document-Driven
   These are the commonly used DSSs and operate on specific keyword search either on WWW or documents or web-based client/server. This helps the user to save time by document analysis depending on the requirements.
4. Knowledge-Driven
   Knowledge-driven DSS are support systems that are designed to mine information from stored knowledge bases of gathered procedures, facts, rules, etc. Data mining techniques are commonly used in these support systems. The typical deployment technology used to set up such systems could be client/server systems, the web, or software running on stand-alone PCs.
5. Model-Driven

Model-driven DSS are complex decision support systems used to analyze data in a similar fashion as that of data-driven DSS. Ml/AL models are built to analyze data and optimize the decision time in order to produce accurate and reliable results. These DSSs can be set up via software/hardware in stand-alone PCs, client/server systems, the web, or APIs.

The application of DSS has found scope in diverse scenarios ranging from marketing, medical health, education, finance, customer support, agriculture, flight systems, industrial process, and beyond.

8.2 INTELLIGENT AGRICULTURAL DECISION SUPPORT SYSTEMS (ADSS)

Farmers may encounter various issues when relaying the right decisions in activities relating to the economy, crop, sowing and harvest, livestock, or environment. Present-day farming decision-making processes have become quite complex because of various external factors affecting the farming system. Due to the use of sensors, satellites, GIS, agri-drones, robots, sophisticated machinery, and IoT (i.e. a digital agriculture) substantial information flow has occurred. Managing such data and proving feasible solutions for crop, disease, or harvesting matters is becoming a fascinating area of research for the government, scientists, and corporate sector and has led to the advent of new standards for farming. An agricultural DSS provides all of the tools and techniques required for the decision process under one roof; therefore, it is best to optimize massive information and generate outputs for enhanced agricultural production [15], [16]. Smart agricultural DM processes usually require both experience and expertise when it comes to a deep investigation of big data [3]. Agricultural support systems play a key role in 21st-century precision farming, as today's farming systems have become more intricate because of the inclusion of various biological, chemical, and physical systems – a vast information explosion. These programs will aid the farmers in preventing losses by guesswork as well as in gaining more access to minute details and issues. Computer-aided DSSs are capable of dealing with sensitive and complicated data and calculations in a fraction of a second, thus providing an error-free and reliable recommendation to the user [3]. Nonetheless, crop simulation models should not be confused with DSSs [17]. An ADSS can benefit the growth of Agriculture 4.0 by facilitating the collection, organization, and integration of indispensable information for crop production. It analyzes the inputs and recommends the most appropriate solution or action. Mathematical or analytical models, knowledge- and data-driven models are quite frequently used in PA [11]. Decisions taken by an ADSS can be of the following classifications: strategic, tactical, or operational. These three types differ in temporal and spatial scale.

Strategic decisions are effected by farm owners or authorities, who are contracted to this for at least a year, and these decisions are mostly related to change of crop varieties, crop rotation, and change of sowing area. Tactical management decisions are made on daily basis and are concerned with crop health, soil health, nutrient requirement, disease and weather monitoring, and irrigation. Operational decisions encompass timely responses to unheralded events at the crop or within-crop levels, such as postponing a fungicide spray because of rain (Figure 8.2).

8.3 FEATURES AND WORKINGS OF AN INTELLIGENT AGRICULTURAL DECISION SUPPORT SYSTEM (ADSS)

The development of decision-making systems in precision farming has mostly been ignored in the past decades [18], [19]. ADSS is accelerating the advancement of Agriculture 4.0 and has added more functionality of automation. To get the most out of an ADSS, it is important to understand its workings [11] – which follows the four "W" questions, as mentioned above. Decision-making starts with identifying the specific problem to be addressed – for example when irrigating a crop, relevant information and data will be gathered and stored (e.g. soil moisture, amount of rain, crop stage, and weather); techniques will be used to impute data and clean it from unnecessary noise. This data will be analyzed and interpreted using either statistical or cognitive approaches or rules, as described in the previous chapter, and the most possible and appropriate set of realistic solutions will be recommended in the form of a decision. The decision made by the support system should be beneficial, cost-effective, easy to implement, and in accordance with technical and legal constraints. The decision

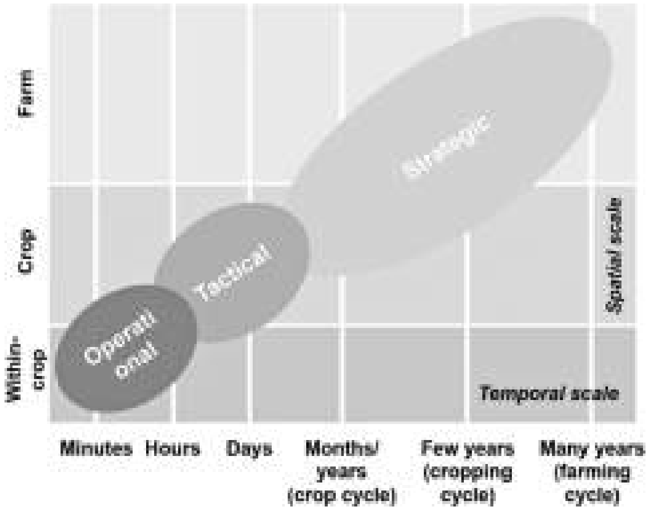

FIGURE 8.2 Decision-Making in ADSS [1].

phase marks the end of the problem-solving process. Each step should be followed in order to reach the best decision. This whole problem-solving process is supported by the three important components of a DSS – precisely, the database (or knowledge base or the data storage component), the model (the decision context and model development as per user criteria), and the user interface (to display outputs in the form of a computer, mobile, website, etc.) [14]. The choice of hardware, platforms, or the usage of developing language shall be customized to suit the needs of farmers, or one should trust the skills of a DSS developer or programmer. Figure 8.3 further illustrates the abovementioned operations:

An efficient decision support system is characterized by the following advantageous features depending on the area of its application [20]:

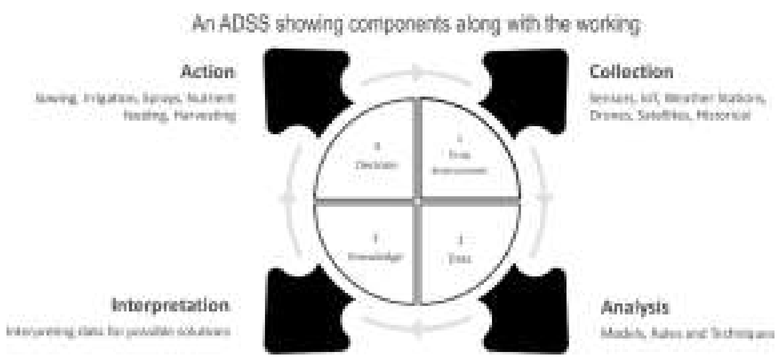

FIGURE 8.3 An ADSS Showing Components along with the Workings, Modified from [11].

1. Competent in making reliable and realistic decisions
2. Able to decide depending on real-time requirements
3. Adept in managing collected data on a cloud or a database
4. Capable of searching or analyzing collected information without consuming much time
5. Proficient in providing support for big data and interpreting analytical and modeling techniques
6. Versed in automating the integration of all of the outputs of each working phase to produce the best decision
7. Equipped in promptly notifying users in the form of SMS, graphs, or other alerts, as defined
8. Intelligent enough to save the decision history for farmer reference and also updates this frequently

DSSs have fairly contributed to precision farming as other developed support systems have hardly been practical because of the high-cost burden on the farmer, lack of trust, inexperience, limited functionalities, and other unexpected effects [21], [22]. Economic benefits arising from the use of DSSs have not been appreciable and, thus, the direct adoption of ADSS is truly weak at only up to 3% of professional farmers in a single country [23], and the indirect adoption or service provided by the government or agricultural departments is growing at a good pace [24]. Efforts are still needed to push for the popularity of ADSS in managing agricultural tasks. A trade-off has to be achieved in the development of support systems that are multipurpose, affordable, and quick to respond.

8.4 INTELLIGENT DECISION-MAKING USING AI, ML, AND IoT FOR FARMERS

DSSs which carries out heuristic and cognitive decision-making and are based on AI, ML, or other intelligent agents' technologies are called intelligent decision support systems (IDSS). The growing field of decision engineering considers the decision as an engineered object that uses engineering design and develops rules for coming up with decisions [25]. An IDSS should act like a human consultant: it primarily serves as support for decision-makers by using gathered data and interpreting different circumstances and subsequently proposing appropriate recommendations and actions. The intention of AI-ML techniques and data collection sources like IoT and sensors is only to improve task performance in terms of minimizing time and human interaction while maximizing accuracy with the decision system [26]. A well-built knowledge base improves the consistency of IDSS when logical and cognitive processes are applied to decide upon uncertain and random phenomenon [27]. A range of AI and ML techniques as explained in previous chapters are applied as required by an application. The decision science in precision farming has reached new heights with the help of intelligent agent approaches.

8.4.1 The Right Information at the Right Time for the Right Decision

Different farming decisions will call for different types of input information. For example, the task of irrigating a field will require both spatial and temporal, site-specific inputs like the type of crop, its water requirements, level of moisture, and weather data. Automated weather stations with soil moisture sensors and other site-specific information (e.g. type of soil, location) facilitate this kind of information. Any errors, time lag, and uncertainty will lead to wrong decisions. The IDSS is based on this surrogate information; the right information should be supplied at the right time for right decisions.

8.4.2 Some Common Agricultural DSS

For global sustainable agriculture, crop production, improvement of farm income, and the reduction of hazardous effects on the environment are the three goals of Agriculture 4.0 [28]. DSSs are an effective tool in achieving these goals. Integrated farming (whole farm approach), integrated production (focus on crops), and integrated crop management (focus on the health of crops) have been approved to shape and perform farming activities in accordance with the site-specific farm needs [29]. The development of multipurpose ADSS has been advanced globally for diverse applications, including the incorporation of different technologies for high-precision decision-making. For various applications like seed sowing, harvesting, price forecasting, irrigation management, weather forecast, smooth operation of machinery, livestock rearing, transportation, storage, variable fertilizer application, chemical spray, among others, different DSS have been made by researchers and private organizations. With the initiation of the Digital India Revolution, many states of the country have now invested in the development of digital decision support systems for farmers. The Department of Agricultural Research and Education (DARE) and the Indian Council of Agricultural Research (ICAR) have started the implementation of DSS and has made data available to all those under the National Data Sharing and Accessibility Policy, 2012, and support systems [30] like Rainbow, Gramseva: Kisan (Mandi Prices), Market Watch, Mandi Trades, U-Agri (CDAC), Krishi Vigan Kendras were set up to enrich agriculture. Private sectors have also pioneered intelligent, self-evolving systems such as smartfarm (CropIn), Fasal [31], but these are usually not affordable. Policy briefs survey reports from ICAR-NAARM (National Academy of Agricultural Research and Management) show the positivity of Indian farmers regarding the popularity of DSS and smart farming approaches like IoT and AI [32]. Similar attempts have been done globally: the Food and Agriculture Organization of the United Nations has significantly contributed to the decision engineering sector (CropWAT for irrigation management, CLIMWAT, Crop Information system) [33]; the USDA-ARS Agricultural Systems Research Unit (ASRU), in a collaborative effort with the Colorado State University (CSU); (Great Plains Framework for Agricultural Resource Management (GPFARM)); Australian based

DSS: (Whopper Cropper; Yield Prophet); livestock production and management (GrazFeed); weather and climate forecasting (Rainfall Reliability Wizard; water and land) [34]; crop growth, irrigation, nutrient management, and, most importantly, CottonLOGIC for the Cotton crop); Morocco-based nutrient management (Planning Land Applications of Nutrients for Efficiency and the Environment (PLANET)); Switzerland pest manage system (SOPRA); US-based (CLIMEX) [35]; TropRice for integrated rice crop management; Decision Support System for Agro-technology Transfer (DSSAT) for multipurpose crop management [36], [37]; web-based multipurpose DSS for weather, crop, and disease management by the New York State Integrated Pest Management Program Network for Environment; Weather Application, Network for Environment, and Weather Applications in collaboration with Cornell University [38] are some notable and commonly used support systems.

8.5 CONCLUSION

ADSSs have become a major element for the 21st-century farming strategy. With further innovation in smart hardware and software as well as the need to grow more food, DSS has developed into something more valuable. Combining all of the processes – from data fusion, storage, interpretation, to decision-making – DSS has become more robust, ergonomic, user-friendly, and accurate. With enhanced GUI or easy web-based interfaces that are accessible on smartphones and cheap internet facilities, farm management has become convenient, and all of the information is available with one tap on a screen. The use of

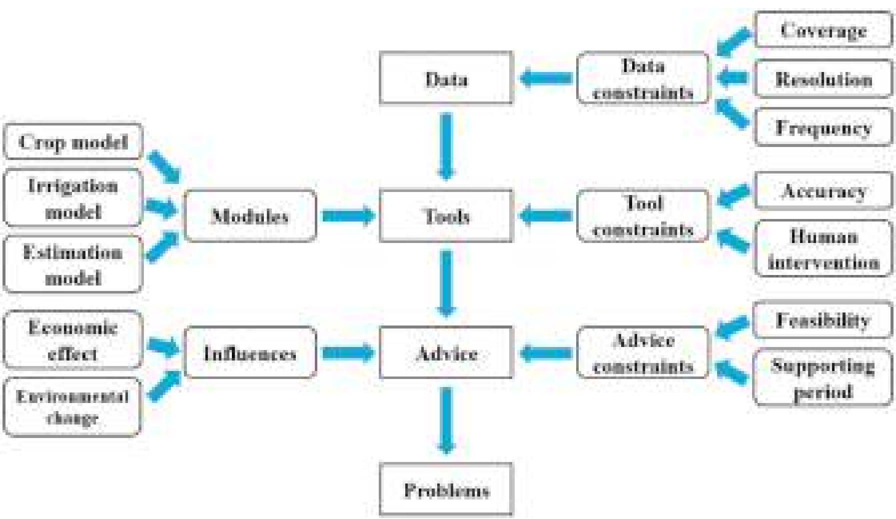

FIGURE 8.4 ADSS Framework [4].

high-resolution spatial or image datasets and mining using computer vision is still new, and many competitors are thriving to succeed in the business. The more optimized and effective techniques are employed, the more successful a DSS will be among end-users. An ADSS can relatively affect the performance of a farming system and may be susceptible to confusion, misunderstanding, or wrong analysis. Major revisions are still required in order to enable the decision system in dealing with site-specific or plant-part-specific operations and take decisions at a micro-scale. A shift in trend towards more real-time-based decisions done at a lesser cost has to take place.

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9 Agriculture 5.0 – The Future

9.1 INTRODUCTION TO AGRICULTURE 4.0

History has witnessed profound effects due to the industrial revolutions (IR); some of which were unforeseen and brought enormous changes. All of the industrial revolutions are shown in chronological order in Figure 9.1 below, while their key attributes are listed in Figure 9.2 and illustrated in Figure 9.3 [1]:

The term "Fourth Industrial Revolution" or "4IR" was coined by Professor Klaus Schwab, the founder and executive chairman of "The World Economic Forum" in his book. The "Fourth Industrial Revolution (4IR)" includes all emerging and disruptive technologies such as artificial intelligence (AI), the Internet of Things (IoT), machine learning, deep learning, artificial neural networks, blockchain, cloud computing, edge-fog computing, drones, etc. The ingenious methods adopted have transformed ordinary objects into smart elements that can be connected to many other devices and possess the capabilities of interoperability to adapt to many systems, thereby, possessing the high potential to make a positive impact on productivity and profitability of the agricultural sector [2].

The Fourth Industrial Revolution is also known as the era of cyber-physical systems (CPS) that are heavily backed by information technology. It is also called **Industry 4.0** and has been able to solve the prevailing problems with these latest technologies [3], [4].

In Industry 4.0, technologies implemented in the agricultural sector have been a real success, and this novel idea has led to certain unimaginable improvements. Agriculture sustaining these changes and adapting according to Industry 4.0 technologies has given rise to the concept of **Agriculture 4.0** [5]. Work was done in the context of designing, developing, and implementing technologies like artificial intelligence (AI), the Internet of Things (IoT), machine learning, deep learning, artificial neural networks, blockchain, big data, drones, robotics, and solar energy was termed Agricultural 4.0. [6]

The increasing demands of the agriculture sector were counterbalanced in Agriculture 4.0 by reinforcing agricultural systems with WSN, IoT, AI systems, etc. Therefore, it accelerated the journey towards smart agriculture and precision agriculture [7]–[9]. Age-old limitations and issues in agriculture were solved because the scientific approaches became more convenient and accessible in Agriculture 4.0 [4], [7]. Agricultural 4.0 has been able to provide for economic farming while increasing yields and productivity [10].

Effective management has been achieved with the introduction of IoT and ML in agricultural practices [8]. Agriculture 4.0 utilizes a decision support system

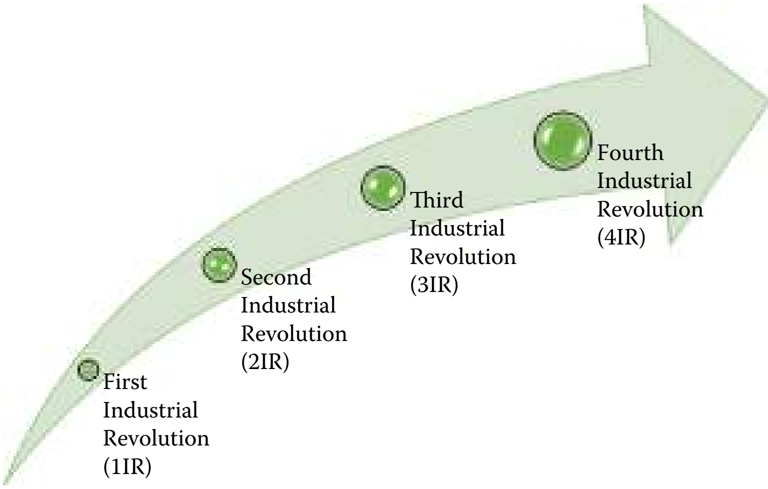

FIGURE 9.1 Industrial Revolutions in Chronological Order

(DSS) in addition to other systems that are required to contribute information to DSS in order to predict weather and the impact of climate on crops and soil [11]. Agriculture 4.0 has been the gateway for introducing fully data-driven systems in agriculture. This has been explained in depth in Chapter 6 of this book.

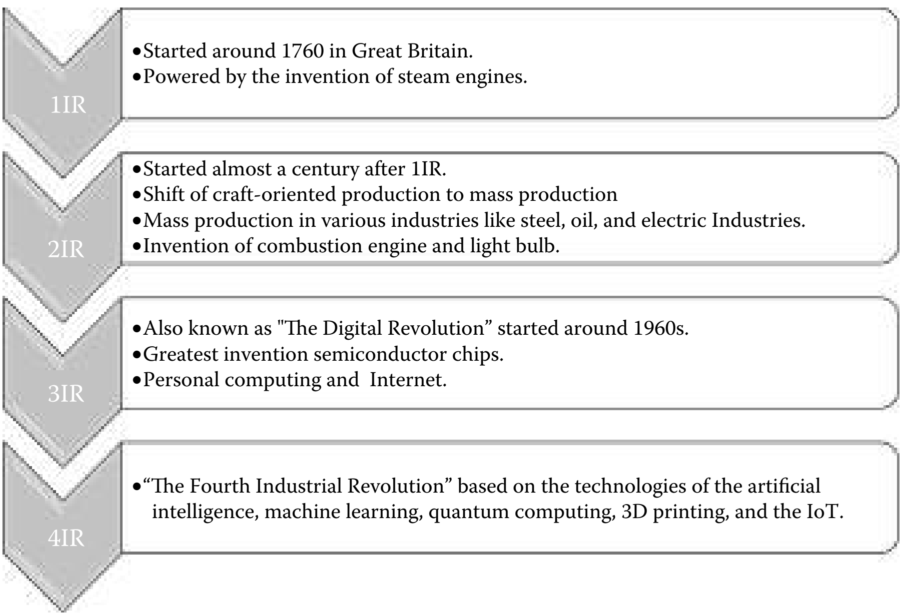

FIGURE 9.2 Industrial Revolutions and Their Key Attributes

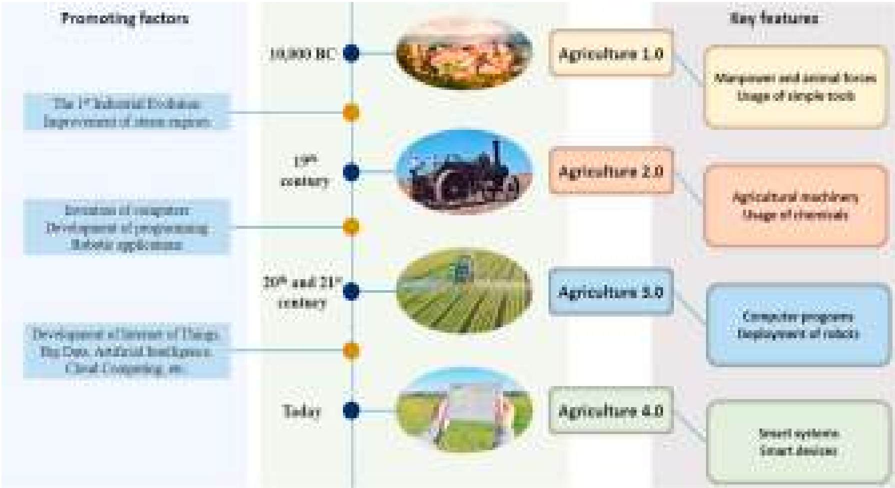

FIGURE 9.3 Transition to Agriculture 4.0 Modified from (Zhai *et al*. 2020) [1].

Reduced food wastes and greater eco-efficiency are its primary goals [12]–[14]. There has been an exponential growth of the economy because of the design, development, and implementation of smart agricultural systems all over the globe [15]. Furthermore, this has transformed agricultural domain [5], [15], [16].

9.2 NANOTECHNOLOGY AND SMART FARMING

Nanoscience and nanotechnology are the study and application of extremely small things, referred to as "nano" size. Nanotechnology is science, engineering, and technology conducted at the nanoscale, which is about 1 to 100 nanometers. The concept of nanoscience was proposed by physicist Richard Feynman at an American Physical Society meeting at the California Institute of Technology (CalTech) on December 29, 1959. It was discovered that particles of some elements at nano-size surprisingly exhibit different attributes and functioning as compared to their large-size counterparts. Professor Norio Taniguchi coined the term nanotechnology. In the 1980s, two major breakthroughs like the scanning tunneling microscope in 1981 and the discovery of fullerenes in 1985 by Harry Kroto, Richard Smalley, and Robert Curl, sparked the growth of nanotechnology in the modern era. Nanomaterials have changed the landscape of the development of electronic devices and also entered other areas like health, agriculture, rocket building, etc.

9.2.1 Applications of Nanotechnology in Agriculture 5.0

At present, the United States of America has invested US$3.7 billion through the National Nanotechnology Initiative (NNI) [17]. The USA is followed by Japan and the European Union, and these countries have abundant funds – US$750 million and US$1.2 billion including individual country contributions, respectively per year. Today, more than 400 companies in the world are active in nanotechnology research and development, and this number is expected to rise to more than 1,000 in the next ten years [17].

- Fertilizer manufacturing: Chemical fertilizers with nanocoatings like sulfur or TiO_2 are prepared for a high rate of dissolution, sustained release of fertilizer which helps in proper absorption by plant roots rather than getting washed off, thus reducing costs and efficiently managing fertilizers and environmental damage [18], [19].
- Silver and gold nanoparticles are mixed with natural biofertilizers like *Bacillus subtilis* and *Paenibacillus elgii* and have become more efficient as these are only required in minute amounts (e.g. one liter for several hectares of a crop) [20], [21].
- Foliar supply of nanoformulations of micronutrients like manganese, copper, boron, iron, molybdenum, zinc, etc. are sprayed or mixed with crop soil.
- Insect and pest management: Applications of various types of nanoparticles, such as silver nanoparticles, aluminum oxide, zinc oxide, and titanium dioxide, in an attempt to control rice weevil (caused by *Sitophilus oryzae*) and grasserie disease in silkworm (caused by Bombyxmori and baculovirus BmNPV (*B. mori* nuclear polyhedrosis virus) were studied and found useful [22]–[26].
- Fungicide: Antifungal activity of nanoparticles of zinc oxide, silver, and titanium dioxide has been tested for various crop pathogens such as *Macrophomina phaseolina,* and the rate of efficiency was notably high. Silver nanoparticles were discovered to be significantly effective even in the lowest amounts for resistant fungi.
- Nano herbicides: Silver nanoparticles were effective in controlling weeds and herbs like *Eichhornia crassipes*.
- Biosensors: One of the most important contributions of nanotechnology is a rather advanced range of sensors using nanomaterials developed for use in many agricultural tasks [27], [28].

9.3 BLOCKCHAIN-SECURING THE AGRICULTURE VALUE CHAIN

In Agriculture 5.0, horticultural big data is growing rapidly and plays a distinctive and critical role in production increment and sustainability. Information and communications technology (ICT)-based tools and techniques have provided a significant breakthrough in the collection, managing, analysis, and decision-making of data [29], [30]. These activities benefit farmers in terms of gaining more control over the farm and related activities to be able to produce more in an eco-friendly manner [31], [32]. Unfortunately, the biased use of the generated and collected data has made such efforts unreachable for farmers. It is every organization's goal to use and interpolate the data to suit need and greed, thus ignoring the main stakeholders who are the growers [33]. To avoid such discrimination, the concept of blockchain entered the scene.

A blockchain is a shared ledger or Open Distributed Ledger Technology (ODLT). It can also be named as "one big ledger in the cloud." The users can add information or update this on the basis of the leftover quantity of a particular product permanently. These records of information and technology are referred to as blocks. Blocks are hack-proof and quite secure. Information related to any product, whether valuable or otherwise, can be saved here through the internet. Any change in a block has to be approved by the maximum number of stakeholder parties [34], [35]. Blockchain is a transformative ICT that has the potential to revolutionize how data is used for agriculture [36]. The blockchain represents one of the most promising technologies in providing more consistency in the wide areas of the agricultural industry. Whether it is applied to managing warehouses, silos, and supply chains more intelligently or utilized in the field as a tool to transmit real-time data about crops and livestock, there are few aspects of an agricultural operation that would not benefit in one form or another from blockchain technology [30], [37], [38].

9.3.1 Possible Applications of Blockchain in Agriculture 5.0

The following are the notable contributions of blockchain towards Agriculture 5.0 [39]–[42]:

1. Farmers, consumers, and retailers will be able to register and share information with maximum safety, transparency, and speed in chronological order.
2. The blocks will be visible to all of the parties in the blockchain, and each party has the freedom of accepting or rejecting the information.
3. All of the information about the entire agricultural event cycle in the blockchain will help the dissemination of a transparent and trustworthy source of knowledge for the farmers.
4. Real-time data about the seed quality, soil moisture, climate, and environment-related data, payments, demand, and sale price, among other things, shall be available to farmers under one platform.
5. Blockchain will help in establishing a direct link between farmers and consumers/retailers. It will empower small farmers to organize themselves and work together to reach the market without requiring any help from middlemen.
6. This will reduce the problems of low income, as blockchain will provide transparency in the supply chain, thus enabling farmers to earn the real price for their produce.
7. This brings forth an effective supply of products, fair pricing, food supply chain, and improved product tracking. It will also facilitate farmers to do real-time management of the stock.
8. Information directly from seed procurement to harvest to sale at the point

of sale (POS) system can be stored on the blockchain. This will aid producers and consumers in quantifying, monitoring, and controlling the dangers during the agriculture chain as well as assisting in alleviating rural distress in developing countries like India.

9. Prominent uses of Blockchain help agriculturalists in traceability (or checking the journey of their product); crop insurance (insuring their crops and claiming damages with insurance companies); transactions (simplifying billing, taxes, annual audits); optimized food supply chain, food safety, retail, and marketing.
10. Some famous blockchain start-ups are AgriChain, AgriDigital, AgriLedger, Worldcovr, etc. [43].

9.4 EDGE-FOG COMPUTING FOR SMART FARMING

After the implementation of cloud computing in various scenarios like IoT, field experts made a thorough assessment in order to find the limitations and areas where cloud computing could be improved [44]. It was concluded that, even though a cloud provided benefits like high computing performance, huge storage, easy and economical connectivity, the performance of cloud computing suffered due to the massive rise in devices, data, and communication involved in networks. Delays (high latency) caused by centralized resources and the distance between devices and the cloud.

Fog and edge computing were created to overcome/mitigate the limitations of cloud computing. Some of the widely accepted explanations are given below:

- Edge Computing: As the name suggests, "edge" refers to the end nodes of a network system. The aim of edge computing is to move the processing of data as close to the source as possible so that it reduces overall traffic that will be sent to the cloud. Thus, the distance covered by the data from source to a processing site is reduced which, in turn, reduces the time (low latency). This modification in the working of the system causes a positive impact on the overall speed, quality, and performance.
- Fog Computing: This determines the workings of edge computing. It provides the necessary resources in the system in order to shift computing closer to the edges. It enables storage, computing, and network services between the edges and cloud centers. Hence, it upgrades the efficiency of the system.

As there are many opinions about edge and fog computing, some believe that edge and fog computing are the same, as the concept to localize computing (that usually, a cloud should perform) in a network is similar for both.

This difference in opinions has led to a mutually accepted conclusion that is based on the location of data processing when it comes to being categorized as edge or fog.

Edge: In this case, the data processing takes place at the edges themselves or on the gateways that are closer to the edges.

Fog: On the other hand, data processing is done in data centers that are located comparatively at a greater distance than that of an edge computing system but necessarily closer than cloud computing.

Some of the important characteristics of edge/fog computing are [45], [46]:

a. Heterogeneity
b. Excellent interoperability
c. Wide geographical distribution
d. Provisions for edge processing and storage
e. Better service quality in comparison to normal IoT endpoints
f. Real-time interaction (comparatively faster than cloud)
g. Support for large-scale sensor networks

Table 9.1 mentions the main differences between cloud computing and edge computing below [44]:

9.5 ROLE OF BIG DATA IN AGRICULTURE

9.5.1 Introduction to Big Data

The world today is generating an enormous amount of data every second, and this data is constantly being captured and recorded. The sources of data are countless, causing this data to be generated in structured, unstructured, and semi-structured forms. Mostly, the data produced is unstructured, but some of the data is still structured and stored in traditional relational databases or data warehouses. The conventional ways of processing, managing, and analyzing the data has gone through a drastic change due to big data. The traditional systems did not adequately manage the data that was gathered from multiple sources. With the advancement in computing power, AI and ML technologies, deep learning, data

TABLE 9.1
Differences Between Cloud Computing and Edge Computing

Characteristics	Cloud Computing	Edge Computing
Computing capacity	High	Low-medium
Server size and operating mode	Large, centralized servers	Smaller, distributed servers
Application suitability	High computational needs, delay is acceptable	Low latency, requires a real-time operation, high QoS
Communication needs	High – devices require a constant Internet connection	Low – devices obtain cache contents via edge gateway
Deployment planning	Complicated planning	Possible ad hoc deployment with little to no planning

TABLE 9.2
Different Units of Data Size

Data Size Name	Symbol	Value	
Bit	b	1 bit	0.125 bytes
Byte	B	8 bits	1 byte
Kilobyte	KB	1024 bytes	1024 bytes
Megabyte	MB	1024 kilobytes	1,048,576 bytes
Gigabyte	GB	1024 megabytes	1,073,741,824 bytes
Terabyte	TB	1024 gigabytes	1,099,511,627,776 bytes
Petabyte	PB	1024 terabytes	1,125, 899,906,842,624 bytes
Exabyte	EB	1024 petabytes	1,152,921,504,606,846,976 bytes
Zettabyte	ZB	1024 exabytes	1,180,591,620,717,411,303,424 bytes
Yottabyte	YB	1024 zettabytes	1,208,925,819,614,629,174,706,176 bytes

mining techniques, and more, this big data has made remarkable improvements in many sectors – including the agricultural arena.

With the amazing capabilities of deep analysis, revealing trends, finding unseen patterns, discovering hidden correlations, revealing new information, extracting insight, enhancing decision-making and automation, among others. big data has proven to be of immense importance in smart agriculture [47].

9.5.1.1 Defining Big Data

Note: Big data has been defined in various sections of the book across various chapters.

Big data is defined as the tremendous amount of data that cannot be analyzed with the capabilities of traditional systems due to its size (referring to the number of sources that data is derived from) and complexity [48]. The advancements in technologies and the introduction of new disruptive technologies like "cloud computing and storage" affords the scale, speed, and reliability that big data requires in terms of the storage dimension. Massive computations have been possible due to the usage of new or improved sets of tools, technologies, algorithms, and paradigms in AI, ML, deep learning, etc. that support management and analysis of big data in a distributed manner [49].

Apart from the huge amount, of datasets that have volume, velocity, veracity, and variety. Big data is a field associated with the collection, organization, integration, and analysis of this huge data in order to obtain value from it.

The key features of big data include [50]:

- Enabling intersections of various unrelated datasets
- High magnitude processing of enormous unstructured datasets
- Deducing hidden information

9.5.1.2 Big Data Life Cycle

In order to provide the most valuable insights, the following steps are carried out in big data. First, this huge amount of data, which can be of different types, is collected. Then, this heterogeneous data is organized and afterward integrated, and this also involves the preparation and cleaning of data for analysis. After completing all of these steps, the big data is analyzed so as to derive value (any useful insight). Many algorithms of AL, ML, and other technologies are used for data mining.

9.5.2 Characteristics of Big Data (6 V's)

Significant research in the area of big data, including its involvement in various fields, has led to a difference in opinion among various experts. Initially, Doug Laney defined the 3 V's (volume, velocity, and variety) of big data [51]. Nearly after two decades, the advancements in the technologies led to more V's being added to the big data. Currently, there are 6 V's that define the characteristics of big data:

1. Volume:
   The fundamental characteristic of big data is the volume of data associated. This implies that large datasets need to be stored and processed. There is a rapid increase in data growth data leading to a size greater than Zettabytes, Yottabytes, or even more, which makes big data management a task that is unique from traditional data management. This creates a demand for technologies to cope with gigantic data volumes [47], [49], [52].
2. Velocity:
   According to [52] the velocity characteristic of big data refers to two things: speed of growth and speed of transfer. The rate at which the data is generated creates a compulsion for fast collection, ingestion, transformation, loading, and integration processes of data. Velocity can also refer to the rate at which the data is processed and analyzed. It refers to the speed at which data is being transacted, and the exponential growth of data is also associated with the speed of transfer of data [47], [49].
3. Variety:
   Variety refers to the various types of data and data structures that form big data. The data can be structured, unstructured, or semi-structured; therefore, this creates challenges in terms of data integration, transformation, processing, and storage. Furthermore, there are sub-varieties of structured, unstructured, and semi-structured data that add up to the issue.
   Unstructured data has maximum sub-varieties of data, and the fact is that 90% of big data is composed of unstructured data such as audio, images, video files, social media updates, log files, click data, and machine and sensor data [47], [52].
4. Veracity [53]–[57]:

This is the most important characteristic of big data. It defines the accuracy and meaningfulness of big data. Uncertainty in data is typically due to inconsistency, incompleteness, latency ambiguities, approximations, etc. A large amount of data makes it challenging to verify the meaningfulness (i.e. possibility of having valuable information) of the data; otherwise, the data may be useless or inaccurate.
Therefore, we need to find an adequate size of quality data that can provide essential information upon analysis to impact agriculture [47], [58].
5. Variability [54], [55], [57], [59]:
Variability refers to data that is constantly changing, shifting, mutating, and modifying. It is one of the important characteristics of big data. Variability occurs with time, the application that uses it, and obsolescence. Deriving context-related outputs from the big data is the result of its variability [58].
6. Value [53]–[57]:

This characteristic of big data is the reason for its application and worldwide trend. The ultimate goal of using big data is to provide such valuable information that was not traditionally possible before its existence. The technique of big data mining to extract insights is the fundamental value of big data. Big data is a platform that provides value from otherwise worthless data [58].

9.5.3 Types of Big Data

Big data has two major sources depending on its generation. It can be machine-generated and human-generated.

According to the variety of data, there are three major types of big data [49], [60]:

I. Structured: Structured type of big data is one that has a predefined length, format, and schema of datasets; accordingly, it can easily be processed, stored, and retrieved in a standard format. Usually, this contributes to 20% of the total of big data. The data is normally in an appropriate form to be easily stored and readily accessed from the database. Examples include sensors deployed in fields to monitor movement, temperature, light, vibration, pressure, moisture, etc.
II. Unstructured: In this case, the datasets do not follow a particular format and can be in the form of images, videos, audio, etc. This constitutes 80% of the total of big data. At present, the technologies have upgraded to deduce information from such data, as earlier this was not possible. In comparison to structured data, retrieving information from unstructured big data takes more time. Storing data with such variety and complexity requires the use of adequate storage systems.

III. Semi-structured: Semi-structured data is the kind of data that is categorized in between structured and unstructured data, because it sometimes contains both types of data. Semi-structured data is a form of structured data that does not conform with the formal construction of data models associated with relational databases or other forms of data tables; however, it has some organizational properties that make it easier to analyze [61], [62].

9.5.3.1 Some Other Types of Big Data

- Real-time data
- Natural language data
- Time series data
- Event data
- Network data
- Linked data

9.5.4 Advantages of Big Data

Big data has been a boon in the current scenario of world technologies as it has contributed a new significant dimension in the science of data analysis, mining, and decision support sciences. Big data analytics includes the methods and devices used to deduce information into meaningful findings by extrapolative/interpolative trend analysis, which is the process of using the data acquired to predict trends within and outside of the data range [48].

Data science is a multidisciplinary science, and the corresponding analytics possess the same traits [50]. Advanced analytic techniques include statistical modeling, data/text mining, machine learning, pattern matching, forecasting, visualization, semantic analysis, sentiment analysis, network and cluster analysis, multivariate statistics, graph analysis, simulation, complex event processing, and neural networks [63]. Examples of data analytics tools are NoSQL, Hadoop, R, etc. Hadoop is widely used because it is open-source.

The agricultural dimension of big data predictive analysis has been explained in detail in the chapter on "Data-Driven Smart Farming" of this book.

9.5.5 Few Applications of Big Data

Some of the areas where big data has a significant role are mentioned below [64]:

- Government
- International development
- Healthcare
- Education
- Media

- Insurance
- Internet of Things (IoT)
- Information technology
- Agriculture

9.5.6 Agricultural Big Data

The data generated by the technologies like sensors, GIS, IoT, smart equipment, drones, etc. in Agriculture 5.0 is called agricultural or horticultural big data. There are diverse forms of data constituting agricultural big data due to the multiple sources of origin. Important examples include the historical data that provides insights for crop selection of a particular year and weather conditions predictions. Other examples are the real-time data generated from the sensors (i.e.sensor data). All of the 6 V's of big data are important in agriculture and help in providing actionable insights to improving overall agriculture. This has also paved the way for AI-powered machines to be embedded in agriculture. The data generated from devices like sensors, GPS, satellites, IoT systems, etc. heightens pertinent knowledge to further improve the field. Agricultural big data analysis plays a crucial role, because it is the root cause for the data-driven Agriculture 5.0. The various important roles of agricultural big data have been reflected in "Section 3.9.1. The Integration of Big Data into Smart Agriculture" and also in the previous chapters of this book: Data-Driven Smart Farming and Intelligent Agricultural Decision Support Systems [48].

9.5.7 Uses of Agricultural Big Data

Big data has prominent applications in Agriculture 5.0; therefore, it is also referred to as big data-driven farming. Big data supports higher quality and better-informed decisions for both production as well as business. To summarize, a few contributions of big data in the agricultural arena are listed below:

I. Yield/pest/disease/weather predictions
II. Selection of suitable hybrids
III. Optimal farming decisions
IV. Crop recommendations
V. Intercropping recommendations
VI. Market price and profitability analysis
VII. Policy recommendations
VIII. Operation/equipment/risk management
IX. Efficient farming practices

9.6 TRANSITION TO AGRICULTURE 5.0

From primitive times, the primary motivation of agriculture has been to feed the population, but with the advancement in science and technology, the priority has shifted to nourishing the population. Due to the explosion in world population, the demand has correspondingly increased. The industrial revolutions have always produced a breakthrough in the agricultural arena. The implementation of precision agriculture, digital agriculture, smart agriculture, intelligent agriculture, and finally, the paradigm shift towards "smart intelligent precision agriculture" have all been able to achieve aims to a great magnitude. These have revolutionized to meet this growing demand and prepare for the future as well. As formerly discussed in various previous chapters of the book, agriculture has been transformed by technologies at every stage in the past. Modern agriculture is completely tech-driven and has a lot to adopt. The section "Smart Intelligent Precision Agriculture" in Chapter 2 is referred to as Agriculture 5.0. This entails the data-driven Agriculture 4.0 with a reinforcement provided by AI and its subsets like machine learning and deep learning. Robotics and artificial intelligence (AI) help in mitigating bigger challenges which have been quite complicated for humans since the past and hence, spur big solutions through disruptive technologies. Smart farming, also known as data-driven farming, makes optimal decisions done only after rigorous analysis of the big data. The application of robotics to agriculture has risen to a new platform due to highly accurate algorithms by AI. Agriculture 5.0 is in the developing phase, and, with the advancement of AI, it is surely going to be accelerated. Thus, Agriculture 5.0 is a way paved for more sustainable agriculture ahead.

9.7 CONCLUSION

With more innovations and research developments, the agricultural sector is becoming more modernized every day. All of the above-discussed technologies are going to help us achieve the goals of an abundance of food with the reduction of environmental damage. These technologies have impressively performed when applied to farming tasks. The objective of doubling the income of farmers with fewer inputs is now a reality. At present, the Agriculture 4.0 revolution will soon achieve another milestone and will be referred to as Agriculture 5.0. In this stage, farmer income will increase, and he will be able to control his farming practices accordingly with the help of these tools and techniques.

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