ARTIFICIAL INTELLIGENCE AND SMART AGRICULTURE TECHNOLOGY

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Chapter 1

Smart Farming Using Artificial Intelligence, the Internet of Things, and Robotics: A Comprehensive Review

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1.1 Introduction

Agriculture continues to remain fundamental to the global economy, with 60% of the world's population relying on it for survival. The Food and Agriculture Organization (FAO) of the United Nations has stated that 5 billion hectares of land, which is 38% of the global land surface, is currently employed in agriculture and related activities. Though this figure seems large, each and every aspect of agricultural activities face

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numerous challenges, such as soil testing, efficient planting, controlling weeds, pesticide control, disease treatment, and lack of proper irrigation (Bannerjee et al., 2018). As such, agricultural industries are on the hunt for novel techniques to improve crop yielding and productivity in order to feed the rising population. Smart technologies such as artificial intelligence (AI), the Internet of Things (IoT), and robotics were incorporated into agriculture a few decades ago. They have led to a period of revolution in agriculture and recently have been paid more attention. Although the integration of this trio of smart technologies can maximize farming efficiency, there are some drawbacks that accompany the implementation and commercialization of such automation technologies (Talaviya et al., 2020). This review aims to revise the numerous desirable applications of AI, the IoT, and robotics in various stages of agriculture and present the major challenges and future recommendations for the successful implementation of advanced farming.

1.2 The Role of Artificial Intelligence in Advanced Farming

Artificial intelligence-based technologies support farming by increasing the efficiency of conventional farming and overcoming the challenges and drawbacks faced by traditional farmers. Artificial intelligence (AI) is the process where humans produce artificial machines similar to the human brain but with an ability to deal with larger amounts of data than the human brain. AI directly falls within the computer science field, but it should surpass this boundary to contribute to agriculture (Jha et al., 2019). Various technical devices and instruments have been developed based on AI that have been tested on agricultural fields and optimized. They have been successful in developing various field-steps of agriculture, such as soil testing, weeding, pesticide control, the treating of diseased crops, lack of proper irrigation to match the needs of crops, post-harvest activities such as storage management, optimising storage parameters, etc. Farmers have attained a high output as well as increased quality of output (Talaviya et al., 2020).

On the other hand, AI can be involved in agriculture to mitigate the environmental concern raised due to unfavourable agricultural activities, such as the heavy usage of pesticides, uncontrolled irrigation resulting in loss of water, and water being polluted with fertilizers. The implementation of AI would help in both these ways (Jha et al., 2019). There have been various AI systems proposed and developed by various scientists for various plantations in the past (Bannerjee et al., 2018).

The foremost objective of utilizing AI-based technologies is to reduce the labour force needed to achieve the required yield. Also, questions unanswered by humans are easily attended to by AI-based devices due to their ability to gather large amounts of data from governmental websites up to the real-time field data and analyse them. They can then provide suggestions to problems that would take a lot of time and high-end skills if they were to be made by humans. AI requires training with the biological skills of the farmer and *vice versa*; hence, farmers with the required skills will also need to be trained with these AI technologies (Talaviya et al., 2020).

1.2.1 The Fundamentals of AI Technologies Involved in Agriculture

The foremost step in involving AI in any field is machine learning. The data that needs to be processed should be fed in a machine-readable manner, and the processed solution should be delivered in a human language. As the AI-based machine processes the fed data, it should be able to gather information from the directed databases to meet the problem that has arisen. On occasion, real-time data would be needed for the AI to arrive at a conclusion, where the AI should be competent enough to read the real-time parameters. Weather prediction is an important factor needed to make decisions about the cropping season.

Chatbots are devices that virtually assist farmers with less experience of interaction with technologies by engaging them in conversations. Unmanned aerial vehicles (UAVs) are popular among governmental and institutional officers of farming for detecting any potential harm to the fields, such as the spreading of forest fires, pest invasions, pathogen attacks, and many more by geolocalization (Talaviya et al., 2020).

Neuro-fuzzy logic, fuzzy logic, expert systems, and artificial neural networks (ANNs) are four methods designed to solve problems (Jha et al., 2019). ANNs are the most common method utilized when designing AI-based technologies. An ANN simulates the processes within a human brain in a machine. In the brain, electric signals pass through neurons by axons and synapses. Various algorithms, such as delta-bar-delta, Silva, and Almeida, are used. The difference between conventional computer programmes and these algorithms is that this method allows the machine to perform an inbuilt task (Jha et al., 2019). A hardware-software interface should be built for the user-friendly functioning of the machine by farmers and other stakeholders. “Embedded systems” are machines into which software is fed.

1.2.2 AI in Crop or Seed Selection

High vigour, good germination, and the seedling emergence rate of seeds have always ensured emergence even under varying agricultural conditions and have been the key to optimising yields and ensuring uniformity in production (TeKrony & Egli, 1991). Traditionally, farmers have optimised seed choice based on experience, and any laboratory experiments for seed-choice optimisation are laborious and prone to error. The way that individual seed varieties react to different weather conditions and disease resistance, etc., are understood by AI technical devices by analysing the previous data to a greater extent than could be accessed by a general farmer.

SeedGerm is a phenotyping platform developed from automated seed imaging and phenotypic analysis based on machine learning. The core algorithm of SeedGerm has been developed with features such as background remover, feature extraction and germination detection, and measurements of traits. The hardware design of the SeedGerm system consists of a translucent plastic box and an overhead image sensor. The seed imaging module of SeedGerm ensures high-throughput imaging, which also enables the removal of background. The system also consists of environmental sensors that sense ambient temperature and humidity. SeedGerm is capable of germination scoring and measuring morphological changes, which in turn scores seedling vigour, and hence could analyse the performance of seed batches. These traits could be used by officials in issuing germination certificates (Colmer et al., 2020). A novel method named crop selection method (CSM) was proposed by Kumar et al. (2015).

1.2.3 AI in Crop Management Practices

Sensors and embedded systems have been developed that support the growth conditions in a growth chamber, such as light intensity, humidity, and O_2 and CO_2 levels. They can control crop conditions per prevailing crop growth data in real-time to match optimised parameters (Lakhiar et al., 2018). Trace Genomics is a technological firm that extracts DNA from the soil samples of agricultural lands and quantifies the microbes dwelling within. The data from the soil is analysed with machine-learning technologies. This biological data is combined with the chemical parameters of the soil sample to finally recommend solutions to the farmer, which would be evidence-based on past occurrence data the past. This would help in selecting the best crop to suit the land or *vice versa.*

A continuous and accessible water supply is required for crop cultivation. Due to the scarcity of freshwater, it is highly advised not to exploit more water resources than is necessarily needed by the crop. Hence, AI technologies, which record real-time data regarding soil moisture content and weather conditions, could manipulate the amount of water needed and automate the supply and ceasing of the water (Talaviya et al., 2020). Kumar et al. (2014) listed a few such automated irrigation methods using AI. Mahmood et al. (2016) listed the risks arising due to heavy pesticide usage, which include effects on biodiversity threats, human health, and leaching of excess agrochemicals into waterways, which can cause environmental issues like eutrophication. Facchinetti et al. (2021) designed a small vehicle-like machine called “Rover” to spray pesticide, leading to a reduction of up to 55% in the amount usually sprayed, and improving crop coverage.

1.2.4 AI in Yield Prediction

Prediction models are one of the foremost AI techniques to be readily accepted by farmers, as yield and profit are the major targets of all forms of agriculture. Soil type, soil nutrient content, crop information, and weather conditions are analysed before predicting the yield. Van Klompenburg et al. (2020) has reviewed a large amount of research regarding yield prediction models.

1.2.5 AI in Pest and Weed Management

Partel et al. (2019) describe a method for developing automated machines that could specifically detect weeds and spray them with agrochemicals, which reduces the wastage of weedicide and reduces the exposure of the crop to the agrochemicals. Pasqual and Mansfield, SMARTSOY, and CORAC are examples of pest management systems (Bannerjee et al., 2018).

1.2.6 AI in Storing and Marketing Products

The storage of agricultural products in suited conditions is crucial for maintaining quality before reaching the consumer. Various sensors have been developed in storage chambers for lengthening the post-harvest life of these products. Traditional farmers only understand the conventional markets of their products, but the latest market trends, decisions about the products' price, and information about the consumption pattern of consumers are precisely analysed by market data and can suggest the next round of crops to the farmers (Talaviya et al., 2020).

1.3 The Role of the Internet of Things in Advanced Farming

As we head towards more cultured and urban farming, the necessity and engagement of fresh scientific developments such as IoT-based technology are becoming increasingly vital in diverse farming systems for numerous applications. They help to improve a variety of farming practices in order to increase yield output while preserving or minimizing the impact on the originality of the product.

1.3.1 IoT-Based Soil Sampling

Manufacturers currently present a wide range of sensors and toolkits to support farmers in monitoring the quality of soil and provide solutions to prevent degradation. They enable the intensive care of soil qualities such as water-holding capacity, texture, and absorption rate, which aids in decreasing densification, salinization, acidification, pollution, and erosion by avoiding the overconsumption of fertilizers. The Lab-in-a-Box soil-testing toolkit made by AgroCares is considered to be a comprehensive laboratory in itself due to the extreme services it provides (Ayaz et al., 2019). Any farmer, regardless of lab knowledge, can use it to analyse up to 100 samples per day without having to visit a lab. Remote sensing is currently being utilized to collect regular soil moisture data, which will aid in the analysis of droughts in remote areas. The Soil Moisture and Ocean Salinity (SMOS) satellite, which gives maps detailing the global soil moisture every one to two days, was launched in 2009 for this purpose (Crapolicchio et al., 2010).

In 2014, researchers in Spain employed SMOS L2 to evaluate the soil water deficit index (SWDI) (Pablos et al., 2018). They used a variety of methods to get the soil water parameters with the aim of comparing them to the SWDI calculated from *in situ* data. In addition, the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor is being utilized to scan the different features of soil with the aim of quantifying the danger of land degradation in Sub-Saharan Africa (Zhang et al., 2006). Sensors and vision-based technology aid in determining the distance and depth required for effective seed sowing. To estimate the seed flow rate, many non-contact sensing methods are offered where the sensors are fitted with LEDs that include visible light, infrared, and laser LEDs, along with a radiation reception element. The seed flow rate is calculated using the signal information related to the passing seeds (Ayaz et al., 2019).

1.3.2 IoT-Based Disease and Pest Monitoring

Farmers may drastically decrease their usage of pesticides by accurately recognizing crop pests utilizing IoT-based smart devices, including wireless sensors, drones, and robots. Contemporary IoT-based pest management offers real-time monitoring, disease forecasting, and modelling, making it more fruitful than conventional pest control approaches (Kim et al., 2018). Cutting-edge pest and disease detection techniques depend on image processing, with raw images collected across the farming region using remote sensing satellites or field sensors. Remote sensing imagery typically covers huge areas and provides more effectiveness at a reduced cost. Field sensors, conversely, can support more functions in data collection, such as environmental sampling, plant condition monitoring, and pest threats, in every phase of the crop cycle. IoT-based automatic traps may collect, count, and even describe pest varieties, then upload the data to the cloud for detailed analysis (Ayaz et al., 2019). This IoT-based pest monitoring system is capable of minimizing the total costs while also assisting in the restoration of the natural climate (Oberti et al., 2016).

1.3.3 IoT-Based Fertilization

New IoT-based fertilization technologies aid in the accurate estimation of spatial patterns of fertilizer requirements while requiring minimal labour (Lavanya et al., 2020). The normalized difference vegetation index (NDVI), for instance, which is based entirely on the reflection of visible and near-infrared light from vegetation, examines the status of crop nutrition utilizing satellite images and measures crop health, vegetation vigour, and density (Benincasa et al., 2017). It also helps to analyse soil nutrient levels. Such exact execution can considerably boost fertilizer efficiency while also avoiding environmental side effects. Geo-mapping, GPS accuracy, autonomous vehicles, and variable rate technology (VRT) are now contributing to IoT-based smart fertilization. Besides precision fertilization, other IoT benefits include fertigation (Raut et al., 2017) and chemigation (González-Briones et al., 2018).

1.3.4 IoT-Based Yield Monitoring

A yield monitor developed using IoT-based technologies can be mounted on any associated harvester and connected to the FarmTRX mobile app, which demonstrates real-time harvest data and instantly uploads it to the manufacturers' web-based platform (Ayaz et al., 2019). This app can create high-quality yield maps that the farmer may export to other farm management tools for further analysis. Fruit growth measurement can be really beneficial in the precise evaluation of the quality and production of the yield. Satellite photographs can be a useful tool for monitoring the output of large-scale crops. This method was used to record rice crop production in Myanmar using Sentinel-1A interferometric pictures (Torbick et al., 2017). Colour (RGB) depth photographs are utilized to track the various fruit stages in mango fields (Wang et al., 2017). Similarly, several optical sensors are being used to measure papaya shrinkage, especially during drying conditions (Udomkun et al., 2016).

1.3.5 IoT-Based Irrigation

Embracing upcoming IoT technology is predicted to change the current status of irrigation practices. The application of IoT-based strategies, such as crop water stress index (CWSI) based irrigation management, is projected to lead to a major enhancement in crop efficiency. CWSI computation necessitates the achievement of crop canopy at various times as well as air temperature (Tekelioğlu et al., 2017). A wireless sensor-based monitoring system has been created in which all field sensors are linked to assemble the measured data, which is subsequently delivered to a processing centre where the farm data is analysed using appropriate intelligent software programs. Various other data, such as satellite imaging and meteorological data, are also fed into CWSI models to analyse water needs, and an exclusive irrigation index value is created for each site. Variable rate irrigation (VRI) optimization by CropMetrics, which functions in relation to soil variability or topography and ultimately develops the effectiveness of water usage, is also a good example (LaRue & Fredrick, 2012).

1.3.6 IoT-Based Food Safety and Transportation

Considering the prevailing hunger crisis caused by population growth, there is a significant opportunity to diminish food wastage and enhance food supply by merely adopting a temperature-controlled transportation system. Executing an autonomous system that utilizes wireless sensors to detect and record temperatures electronically, on the other hand, can significantly increase food safety. This approach provides a continuous temperature data stream. Readings can be taken regularly and on time this way, leaving no space for interpretation; in other words, the whole procedure is based solely on facts (Bouzembrak et al., 2019). Furthermore, the recorded data can be kept in the cloud and retrieved from any device connected to the Internet, owing to current technological advancements (Bharati & Mondal, 2021; Podder et al., 2021). Notifications can be delivered in real-time if the temperature exceeds predetermined boundaries, meaning rapid action can be taken to correct the situation. In addition, the IoT provides predictive maintenance by predicting when the monitoring equipment will reach the end of its useful life, allowing it to be substituted before it malfunctions and impacts the quality of products (Popa et al., 2019). Some of the vital technologies utilized and their uses are enumerated in Table 1.1.

Various multipurpose technologies such as cloud computing, communication technologies, etc., are being utilized in IoT-based farming in order to accomplish the

Table 1.1 Vital Technologies and Their Uses in Food Safety and Transportation

Technologies	*Uses*	*References*
ComplianceMate	Monitoring food safety and quality with hazard analysis and critical control points (HACCP). Capturing temperatures in rooms and coolers at every minute when it integrates with Touchblock.	(Booth, 2015)
Laird Sentrius	Helping in developing, customizing, and supporting entire cold chain systems. Handling challenging cold chain environments. Ensuring connectivity and consistency. Making implementations easier, less costly, and most effective.	(Ayaz et al., 2019)
CCP Smart Tag (RC4)	Thorough monitoring solution for the food service and food retail industry. Automating the temperature of the environment. Temperature and other data are interpreted and observed on a service provider cloud platform utilizing mobile and web applications.	(Htet Myint, 2020)
TempReporter	Continuous monitoring of temperature. Logs readings automatically.	(Ayaz et al., 2019)

Table 1.2 Common Mobile Apps and Their Diverse Applications in Farming

Mobile apps	*Applications*
PocketLAI	Irrigation
LandPKS	Soil assessment
AMACA	Machinery/tools
Ecofert	Fertilizer management
AgriMaps	Land management
SnapCard	Spraying applications
SWApp	Irrigation
WeedSmart	Weed management
VillageTree	Pest management
WISE	Irrigation
EVAPO	Irrigation
BioLeaf	Health monitoring
cFertigUAL	Fertigation

Source: Ayaz et al. (2019); Ferguson et al. (2016)

tasks mentioned above. A cloud-based system is adept at handling a broad array of data and formats and can configure these forms for various applications (Tan, 2016). AgJunction has developed an open cloud-based system that collects and distributes data from various precise agriculture controllers, reducing costs and environmental impact (Raj et al., 2021). Additionally, Akisai, Fujitsu's agricultural sector cloud, includes information communication technologies with the intention of elevating the food supply in the next years (Kawakami et al., 2016).

Wi-Fi, LoRaWAN, mobile communication, Zigbee, and Bluetooth are examples of communication technologies that can be used to apply the IoT in advanced farming (Jawad et al., 2017). These technologies allow the automation of the entire agricultural cycle, making agriculture more expedient and effective. Zigbee is extensively utilized for IoT implementation in agriculture among many communication technologies due to its little power consumption, cost-effectiveness and versatility (Farooq et al., 2019). Some of the most commonly used mobile apps and their diverse applications in IoT-based farming are enumerated in Table 1.2.

1.4 The Role of Robotics in Advanced Farming

With technological advancements, robotics applications in digital farming have sparked a surge in interest, transforming typical field activities into innovative technical tasks that are highly beneficial. Various types of robots capable of conducting diverse farming operations, such as planting, field inspection, field data gathering, weed control, precise spraying, and harvesting, have been developed so far, although many are still in the prototype phase.

1.4.1 Robotics in Planting

Planting demands a significant amount of time and effort because the process requires a high level of consistency and precision and typically spans a large agricultural area. For numerous crops, such as corn, wheat, sugarcane, and vegetables, autonomous systems have been established to solve the issues of manual planting (Mahmud et al., 2020; Shi et al., 2019). The Agribot platform was used to create an autonomous seeding robot. An infrared (IR) sensor was employed in this development to verify the integrity of the seed tank, as well as for row identification, and it produced a reasonable outcome in terms of precision in the distance between seeds (Naik et al., 2016). Robots made of galvanized iron in previous research were able to till the soil and sow seeds (Sunitha et al., 2017). Several other robots capable of multitasking, including planting activities, are being used in modern farming (Chandana et al., 2020). As a result, with superior planting quality, the automated process of planting would be much more proficient and suitable for farmers in the near future (Mahmud et al., 2020).

1.4.2 Robotics in Weed Control and Spraying

The most widely used farm duties of field robots are weed control and precise spraying. When compared to blanket spraying, targeted spraying using robots for weed control has given satisfactory outcomes and decreased herbicide consumption to as little as 5–10% (Pinheiro & Gusmo, 2014). Various potential weed robots have been presented and deployed during the past 10 years as the outcome of interdisciplinary cooperation initiatives among several worldwide research groups; however, they are still not fully commercialized. It has been reported that these robots are capable of reducing the use of weed chemicals by 80–90 % (Molina et al., 2011). Some of the robots being used in this sector for various tasks are recorded in Table 1.3.

1.4.3 Robotics in Field Inspection and Data Collection

The use of automation in agricultural inspection required the development of a system that can perform the inspection process without the use of human eyesight. As a result, computer vision is increasingly being utilized to substitute human vision in the examination of plants in agriculture. Computer vision is a cutting-edge image processing technology that has shown promising results and has the potential to replace human eyesight in specific inspection tasks (Ayaz et al., 2019). Autonomous inspection is typically carried out by mounting a camera in a static point on a transportable robot or a drone. The deterrence of diseases and the quality testing of

Table 1.3 Commonly Used Robots and Their Applications for Weed Control and Spraying

Robots	*Applications*	*References*
BoniRob	Weed control for row crops. Field mapping.	(Bakken et al., 2019)
AgBot	Autonomous fertilizer application. Weed detection and sorting. Chemical or mechanical weed control.	(Redhead et al., 2015)
Autonome Roboter	Weed control	(Shamshiri et al., 2018)
Tertill	Weed cutting	(Sanchez & Gallandt, 2020)
HortiBot	Transporting and attaching a variety of weed detection and control tools.	(Fountas et al., 2020)
Kongskilde Robotti	Automated and semi-automated mechanical weed control.	(Bogue, 2016)

commodities will become more precise and effective as a result of the self-governing strategy and its execution in the inspection procedure, ensuring future food security. Scouting robots for data collection involves the substantial utilization of advanced sensors for advanced farming (Patmasari et al., 2018). Listed below in Table 1.4 are some of the robots being used for field inspection and data collection with multiple applications.

1.4.4 Robotics in Harvesting

Increased harvesting efficiency and lower labour costs will assure sophisticated food production yield and affordability. As a result, the implementation of autonomous harvesting using robots should be considered an alternate option to solving expenses and labour unavailability. For fruit detection inside the canopy, the earliest experiments used simple monochrome cameras (Gongal et al., 2015). Many current advancements are being incorporated into harvesting robots, including the autonomous recognition of fruits from manifold images or based on the fusion of colour and 3D features (Barnea et al., 2016), multi-template matching algorithms (Bao et al., 2016), symmetry analysis, combined colour distance method and RGB-D data analysis for apples (Garrido-Novell et al., 2012) and sweet-peppers (Lavanya et al., 2020), stereo vision for the detection of apples, and the usage of convolutional neural networks (Zhao et al., 2016) and deep learning algorithms for the recognition of fruits and evasion of hindrance in very condensed foliage (Zujevs et al., 2015).

Table 1.4 Commonly Used Robots and Their Applications in Field Inspection and Data Collection

Robots	*Applications*	*References*
TrimBot2020	Automatic bush trimming. Rose pruning.	(Shamshiri et al., 2018)
Wall-Ye	Field mapping. Pruning.	(Fountas et al., 2020)
Ladybird	Surveillance and mapping. Classification and detection of different vegetables.	(Bender et al., 2019)
MARS	Optimizing plant-specific precision agriculture.	(Fountas et al., 2020)
SMP S4	Bird and pest control.	(Shamshiri et al., 2018)
Vine agent	Health monitoring of plants.	(Arguenon et al., 2006)
HV-100 Nursery Bot	Moving of plants and potted trees in greenhouses.	(Shamshiri et al., 2018)
VinBot	Autonomous image acquisition. 3D data collection for yield estimation.	(Shamshiri et al., 2018)
Mantis	Field data collection.	(Stein et al., 2016)
GRAPE	Plant detection. Health monitoring. Manipulation of small objects.	(Roure et al., 2017)

The field examination of a self-governing robot for de-leafing cucumber plants introduced a functional model in a high-wire farming structure (Van Henten et al., 2006). Various studies on robot arm motion planning for agricultural harvesting operations have been done in recent years. A motion scheduling system was successfully implemented with a 51% success rate to synchronize the four arms of a robot for an automated kiwi fruit picking system (Udomkun et al., 2016). Apple tree branches were detected with 94% accuracy using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method in Ayaz et al. (2019). Many research studies are currently in progress for developing simple manipulators and multi-robot systems as well.

1.5 The Challenges and Recommendations of Indulging Technologies in Advanced Farming

A higher quantity of food of high quality is needed in the near future due to the rapid rise in population (Ayaz et al., 2019). Hence, both the yield and quality of agricultural production should be increased by the application of technologies into the field.

Even though 2% of the farming population performs better in terms of quantity and quality as they have access to modern technology, the rest of the population struggles to gain a better yield. This is clear to see because developed countries, such as Australia and most countries in Europe, have already been using new technology and equipment over the past five decades and have reached an exponentially higher yield. Thus, it is clear that modern equipment and technology help in obtaining higher yields, as well as making farms environmentally safe and beneficial (Zha, 2020). In light of this scenario, future agriculture is predicted to develop into a high-tech industry, with networked systems benefiting from artificial intelligence and big data capabilities. From sowing to production forecasts, the resulting systems will converge into a single unit where farm machinery and management will be linked. Agriculture may usher in a new era of superfusion by using sophisticated technology such as agricultural robotics, big data, and cloud-computing artificial intelligence.

The major challenge of introducing technology into advanced farming is the lack of proper knowledge of farmers who practice them in the field. Hence, the major recommendation would be to simultaneously educate farmers about the insights of technological devices and produce a proper information base from individual farming lands in order to optimize the devices in the future. Fear of technological devices and automation technologies replacing the needed labour force had created a reluctance towards these technologies among farmers in agriculture. There is a high chance that utilization of these technologies will be avoided as field management and disease management practices, which were historically performed by experienced farmers, are now given by machines. Hence, it is practically observed that young farmers who have more hands-on experiences with the technologies are readily accepting the technologies into their fields than the old farmers. Hence, they should be slowly admitted and introduced to them (Jha et al., 2019).

The creation of autonomous machines such as tractors is not accepted due to safety considerations. Hence, more precise sensors and controlling technologies should be developed in the future. Also, to employ autonomous agricultural machinery in the field, IoT technologies must be combined to ensure agricultural machinery safety (Kim et al., 2020).

Both cultivation and domestication of species are included in agriculture (Harris et al., 2014). As only cultivation is looked upon by many farmers now, the domestication purpose has been greatly left to scientists and agro-technical officers. Hence, the implementation of AI into the field of domestication would make it easier for farmers to use their knowledge about wild varieties and test them for domestication. AI development and involvement have only been limited to areas of agriculture where profit-gain is the major target; however, the minor fields of agriculture such as horticulture, mixed crop-livestock farming, and arboriculture should also be given enough attention to improvise as well as optimize the services provided by those fields.

IoT devices are employed in open surroundings in most agricultural areas, with the exception of greenhouses, where they are directly exposed to hostile conditions.

Safety devices are required in IoT hardware because environmental variables such as rain, high temperature, humidity, and strong wind may affect their performance (Farooq et al., 2020).

Hacking gathered host properties, farm information, and agricultural data, as well as network and communication interruptions, should be avoided in IoT-based agriculture. Since the IoT employs a distributed network of sensor nodes, a single security protocol is insufficient, and it is necessary to plan for data loss (Paul et al., 2020).

The major challenge for sensor development and agricultural robotic technology is the required spatial and resolution data being unable to be measured as they vary extremely and hence pose difficulties in measuring them. The goal of new analytical methods is to extract new knowledge by combining data and fusing disparate information layers. Network applications must be trustworthy and scalable in order to manage these complex systems.

The main difficulties to be disentangled for the generalization of robotics structures are increasing the speed and accuracy of robots for agricultural applications. The progress in the research related to the field is hindered by the lack of substantial budget allocations and funding. Improving sensing (fruit detection), acting (manipulator movement, fruit attachment, detaching, and collecting), and growing systems (leave pruning and plant reshaping) are some of the features that could be vehemently suggested to improve the efficiency.

It should be noted that the development of a cost-effective and efficient agriculture robot necessitates a multidisciplinary approach involving deep learning and intelligent systems, computer science, dynamic control, crop management, sensors and instrumentation, horticultural engineering, software design, mechatronics, and system integration (Rahmadian & Widyartono, 2020). According to an IDTechEx report, by 2023, more types of robots could be seen in the market with the rolling out of robots used in weeding, vegetable and fruit harvesting, strawberry picking, and apple picking.

AI, IoT, and robotics in agriculture are expected to solve a number of challenges and enable higher quality and productivity. However, there is a need for a technology that integrates and applies these technologies to all aspects of farm management. Therefore, research and development in this particular area should be encouraged, and the governments should be ready to invest in the research sector of agriculture for the well-being of their people.

1.6 Conclusion

Machine learning has enabled deep learning into automated technologies to be directed for use in agriculture. Machines communicate with different databases and produce solutions to timely problems faced by farmers. Adopting smart technologies, AI, the IoT, and robotics for various applications in advanced farming can be highly beneficial to farmers. These technologies have reduced the involvement of labour in the processes, thus reducing the number of human-made mistakes as well as optimizing the processes, which have resulted in high efficiency of production as well as high yield. However, future research and development is needed to overcome the shortcomings associated with these smart technologies in advanced farming.

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